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Chapter 1

Preface

Understanding the behavior of financial markets in the future, the interconnectedness of different markets, the impact of different investor groups on financial markets and related topics are exciting and important objects of research in finance.

Therefore, this thesis dedicates its first two chapters to research that contributes to our understanding about the information content in options markets for future moments of single equity and stock index returns.

In Chapter 2, the paper "**The Information Content of Option Demand**" (with Kerstin Kehrle[1]) combines the concept of market sidedness developed by Sarkar and Schwartz (2009) with excess option demand (changes in open interest) to construct a measure of options market sidedness that captures the sign and the magnitude of directional information in public option data.

The motivation for the measure is as follows; directionally informed investors have an incentive to trade in those contracts that provide them with high leverage. This implies that the increase in the open interest of high leverage options (out-of-the money options) should be larger than the change in the open interest of low leverage options (in-the-money options). Additionally, when informed investors have positive information we expect a higher demand for call options than for put options and vice versa in the negative information case. Therefore in order to capture situations characterized by a high degree of positive information we relate changes in the open interest of out-of-the-money (OTM) call options (the most attractive options for investors with positive information) to the

[1]Swiss National Bank

change in open interest of in-the-money (ITM) put option contracts. So our positive information measure is the 30-day rolling correlation between the change in the open interest of OTM call options and the change in open interest of ITM put options. We construct an analogous options market sidedness (OMS) measure for detecting when investors have negative information.

Intuitively, a low value of our measure implies that increases in demand for contracts that are particularly sensitive to information trading are not associated with increases in demand for contracts that are relatively insensitive to information trading. In the terminology of Sarkar and Schwartz (2009) the market is one-sided and is characterized by asymmetric information. On the other hand a high value of our measure indicates that demand for information trading sensitive contracts is also associated with increases in demand for contracts that are information insensitive, the market is two-sided and option demand is more likely driven by heterogeneous beliefs.

To examine whether options market sidedness captures informed trading, we use a dataset of all exchange traded securities at the intersection of OptionMetrics Ivy DB, the CRSP daily return files from January 1996 until December 2009 with more than 5 million observations.

We find that options market sidedness predicts the sign and the magnitude of future returns of the underlying even after controlling for a wide range of factors (including alternative measures of informed trading).

Trading strategies based on options market one-sidedness are highly profitable. Using options market sidedness to select option contracts yields average returns of 22% for OTM calls and 26% for OTM puts over roughly four weeks. To make sure that our results are robust to option bid-ask spreads and the implicit leverage of options we construct long-short equity portfolios based on options market one-sidedness. Our strategies generate monthly risk-adjusted returns of 2.21%.

Further, we study options market sidedness prior and post to M&A announcements to examine whether our measure indicates the presence of significant asymmetric information that is resolved on the announcement date. Consistent with this, we find that our measure decreases prior to the announcement and increases post announcement.

Given that options market sidedness identifies informed trading it is likely that market makers respond to the presence of informed investors. We find that options market one-sidedness is associated with future higher option bid-ask spreads. Additionally, we find that a more one-sided options market predicts violations of put-call parity. These results are consistent with market makers gradually incorporating the information in the demand of informed traders and more generally with the perspective furthered by Garleanu, Pedersen and Poteshman (2009) that demand pressure in options markets should impact prices and price efficiency.

The contribution of this paper is threefold. First, we develop a measure of options market sidedness that identifies the sign and the strength of directional information in publicly available options data. Using changes in open interest to compute our measure of options market sidedness we focus on the part of option demand that is in excess of the demand associated with other trading motives. Second, we show that option demand contains directional information about the underlying. As such we complement Pan and Poteshman (2006) who document using private data that there is directional information in signed option volume but find no evidence for directional information in the public part of their data. Third, we provide evidence that directionally informed option demand impacts options market liquidity and price efficiency.

In Chapter 3 of this dissertation my paper "**Volatility Information in Index Option Demand**" takes the idea of "Options Market Sidedness" to the level of index options and focuses on volatility information in option demand and investor uncertainty. Volatility informed trading in index options has not yet been systematically addressed even though equity index options represent a substantial fraction of the derivatives market. Additionally, the paper studies whether volatility demand in options markets is useful as a measure of investors' uncertainty about the macroeconomy. Intuitively, volatility information related option demand might be high at instances of high aggregate information asymmetry, such as FOMC decisions on adjustments of the target rate or releases of data on unemployment, GDP, consumption or other important macroeconomic aggregates. Hence, the degree of volatility informed option demand might also project investors' uncertainty about macroeconomic news.

To determine whether equity index option demand contains volatility information, I use the concept of option market sidedness as furthered in Kehrle and Puhan (2014) to construct a measure of volatility informed index option demand (OMS^{σ}). The measure has the following intuition; since a common trading strategy to exploit volatility information is the straddle trade volatility informed trading results in a joint excess demand (changes in open interest) for at-the-money (ATM) call and put options with the same maturities (e.g. Ni, Pan and Poteshman 2008). Hence to measure volatility informed trading I relate the changes in open interest of ATM call options to the changes in open interest of ATM put options with the same maturity.

More specifically, OMS^{σ} is a correlation between open interest changes of ATM call and put options pairs that would be part of a straddle strategy in a 30-day backward looking rolling window. The intuition for the measure is that higher values of the measure indicate a stronger comovement of the excess demand in call and put options that would be part of the same straddle trade, which signals in increased volatility informed demand. On the other hand lower values of the measure indicate less trading on information about future volatility.

To investigate whether index option demand contains information about future market volatility and investor uncertainty about the macroeconomy, I use daily CRSP data of the S&P500 stock index (SPX) and data on all option contracts on the index as provided by OptionMetrics Ivy DB from November 2000 until December 2010.

I find that informed excess demand in straddle option pairs has predictive power for future volatility beyond current and lagged volatility and even after controlling for changes in market risk premia, option implied volatilities and other variables. Furthermore, focusing on macroeconomic news announcements as exogenous events of high aggregate uncertainty, I find that the changes in open interest for straddle option pairs are larger and the predictive power of OMS^{σ} for index volatilities is significantly stronger before macronews announcements and decrease after the announcement.

Trading on volatility informed option demand yields annualized Sharpe Ratios for straddle strategies that in some cases almost double the Sharpe Ratios for a long investment in the equity index. Sharpe Ratios (and returns) of the strategies increase with the strength of the volatility informed trading, in particular during periods of high volatility.

The paper also speaks to the relation between informed volatility demand in options and uncertainty about macroeconomic news. I find that a higher demand for straddle option pairs before macroeconomic news announcements predicts larger uncertainty about macroeconomic fundamentals. This implies that OMS^{σ} is a potentially interesting new measure of investor uncertainty about macroeconomic news. However, OMS^{σ} is not informative about the future levels or changes of the macroeconomic fundamentals by themselves (e.g., does not predict GDP or GDP growth).

Finally, the third chapter of my thesis contributes to another important strand of the finance literature, that is studies about corporate financing and investment decisions. The investment timing of firms and the determinants of corporate decisions about the optimal source of funding are central questions in finance that are so multifaceted that they provide incessantly new research questions.

In "**Financing Asset Sales and Business Cycles**" (jointly with Marc Arnold[2] and Dirk Hackbarth[3]), we explore the decision of firms to use asset sales instead of equity issuance in order to invest (financing asset sales). The traditional view in the literature associates non-core asset sales with firms that are financially distressed and use the proceeds of the asset sales to repay debt (e.g. Shleifer and Vishny 1992, Weiss and Wruck 1998) or, alternatively, with financial constraints that create the need for firms to use internal sources of funding in order to invest (e.g. Lang, Poulsen and Stulz 1995, Hovakimian and Titman 2006, Bates 2005).

We start our analysis, by highlighting empirical facts from a sample of U.S. manufacturing firms in Compustat that cannot jointly be explained with the existing motivations for asset sales. In order to explore the determinants of financing asset sales, we focus in the data on the correlation of asset sales and investment and factors that increase this correlation. We document that the correlation between asset sales and investment is sig-

[2]University of St. Gallen
[3]Boston University

nificantly higher (i) for firms with higher leverage, (ii) in bad business cycle states, (iii) for firms with attractive growth opportunities in bad business cycle states and (iv) our results also indicate that unconstrained firms are more likely to use financing asset sales.

Motivated by these stylized facts on financing asset sales, our paper proposes a theory that relates financing asset sales to the wealth transfer problem between equityholders and bondholders and jointly explains the evidence in the data. Firms in our model are financed with equity and risky debt; each firm has a certain amount of assets in place and a growth option. Since the firms are partly financed with risky debt, the decrease in asset volatility of a firm at investment creates the well-known wealth transfer problem between equityholders and bondholders. We argue, based on our model, that selling assets upon investment increases the leverage, which renders debt more risky. The resulting wealth transfer from bondholders to equityholders mitigates the wealth transfer from the equity holders to the bondholders at investment. Since the wealth transfer problem is larger the higher the leverage of the firm is, it is particularly severe in bad states of the business cycle where firm leverage increases. Our model predicts that firms with a higher leverage, firms in a bad business cycle state and firms with attractive growth opportunities in bad states tend to use more financing asset sales. These predictions match jointly the evidence in the data and support our hypothesis that the wealth transfer problem is a potential channel to explain the stylized facts on financing asset sales that we have identified in the data.

We estimate a structural model and use the simulated sample in order to investigate the model-implied correlation between asset sales and investment. The regressions from the simulated sample broadly support the predictions of the model and qualitatively match the evidence on the correlation between asset sales and investment in the Compustat data.

The conclusion of the paper is that financing asset sales are a significant source of investment funding and provide an opportunity for equity holders to mitigate the wealth transfer problem, in particular in bad states of the business cycle.

Chapter 2

The Information Content of Option Demand

joint with Kerstin Kehrle

2.1 Introduction

A body of work in finance has documented the effects of asymmetric information on the functioning of financial markets (e.g., Kyle 1982, Grossman and Stiglitz 1980, Easley and O'Hara 1987). To financial economists and practitioners it is important to accurately determine to what extent there is informed demand in a market at a given point in time. Among other things options provide investors with leverage and therefore we expect informed trading in option markets (see Black 1975, Easley, O'Hara and Srinivas 1998). However, identifying informed demand is challenging since it has to be separated from other trading motives such as hedging and liquidity. To further complicate issues any return predictability associated with a measure of informed trading needs to be separated from other sources of return predictability that are not due to directional information, such as risk premia, volatility information or mispricing.

To deal with these challenges in a direct and easy to implement way, this paper combines the concept of market sidedness developed by Sarkar and Schwartz (2009) with excess option demand (changes in open interest) to construct a measure of options market sidedness that captures the sign and the magnitude of directional information in widely available unsigned option data.[1]

[1]The open interest of a call or put option refers to the total number of outstanding options of a specific contract type. Since the number of outstanding option contracts is endogenous, an increase in the open interest indicates, endogenously, an excess demand for options. The existing literature has primarily used

The motivation for the measure is as follows: Directionally informed investors have an incentive to trade in those contracts that provide them with high leverage. This implies that the increase in the open interest of high leverage options (out-of-the money options) should be larger than the change in the open interest of low leverage options (in-the-money options).[2] Additionally, when informed investors have positive information we expect a higher demand for call options than for put options and vice versa in the negative information case.[3] Therefore in order to capture situations characterized by a high degree of positive information we relate changes in the open interest of out-of-the-money (OTM) call options (the most attractive options for investors with positive information) to the change in open interest of in-the-money (ITM) put option contracts. Specifically our positive information measure is the 30-day rolling correlation between the change in the open interest of OTM call options and the change in open interest of ITM put options.[4] We construct an analogous options market sidedness (OMS) measure for detecting when investors have negative information.

Intuitively, a low value of our measure implies that increases in demand for contracts that are particularly sensitive to information trading are not associated with increases

volume, option prices, bid-ask spreads or implied moments to study informed trading in option markets. However, there are many motives for trade and therefore changes in open interest have advantages over trading volume as a measure of informed demand. For example, liquidity needs and hedging demand results in volume, but may well leave the open interest unchanged (see Section 3.4 for a more detailed description).

[2]There is usually a certain "natural" level of option contract creation and closing, for instance due to synthetic option creation for technical trading strategies that involve as a replication or closing instrument ITM options and the short side of OTM options (see e.g., Lakonishok, Lee, Pearson and Poteshman 2007).

[3]An alternative would be to go short in the opposite contract type. However, this would expose the informed trader to much higher risk, which makes this trading alternative less attractive. In support of this argument, previous work, such as Garleanu, Pedersen and Poteshman (2009), Pan and Poteshman (2006), Lakonishok, Lee, Pearson and Poteshman (2007), Muravyev (2013), Easley, O'Hara and Srinivas (1998), Choy and Wei (2012) or Chesney, Crameri and Mancini (2011), highlights the creation of new long positions in out-of-the-money options as main channel of information related option trading. This is supported by occasional evidence such as in Poteshman (2006) who identifies how informed investors used long out-of-the-money put options of airline companies prior to the 2001 terrorist attacks. Another example is the case of the German Commerzbank where in April 2011 in the week before a recapitalization announcement some investors took large positions in new out-of-the-money puts and realized large profits due to the post announcement stock price decline. Despite the high probability that informed traders create new long positions we can naturally not exclude that informed traders also use different strategies. Incorporating these trades would make our results only stronger but would come at the cost of a much more complicated methodology to measure options market sidedness.

[4]More formally we compute the positive information measure as $OMS^{+} = corr(\Delta OI^{C}_{OTM}, \Delta OI^{P}_{ITM})$, where ΔOI^{C}_{OTM} denote the changes in open interest of OTM call options and ΔOI^{P}_{ITM} the changes in open interest of ITM put options, respectively.

in demand for contracts that are relatively insensitive to information trading. In the terminology of Sarkar and Schwartz (2009) the market is one-sided and is characterized by asymmetric information. On the other hand a high value of our measure indicates that demand for information trading sensitive contracts is also associated with increases in demand for contracts that are information insensitive, the market is two-sided and option demand is more likely driven by heterogeneous beliefs.

To examine whether options market sidedness captures informed trading, we use a dataset of all exchange traded securities at the intersection of OptionMetrics Ivy DB, the CRSP daily return files from January 1996 until December 2009 with more than 5 million observations.

We find that options market sidedness predicts the sign and the magnitude of future returns of the underlying even after controlling for a wide range of factors, including alternative measures of informed trading. A one standard deviation decrease in the OMS^+ (OMS^-) measure predicts an increase (decrease) of future returns of more than 6 basis points on a daily basis and more than 16% annually.

Trading strategies based on options market one-sidedness are highly profitable. Using options market sidedness to select option contracts yields average returns of 27% for OTM calls and 32% for OTM puts over roughly four weeks. To make sure that our results are robust to option bid-ask spreads and the implicit leverage of options we construct long-short equity portfolios based on options market one-sidedness. Our strategies generate monthly risk-adjusted returns of up to 2.22%.

Further, we study options market sidedness prior and post to M&A announcements to examine whether our measure indicates the presence of significant asymmetric information that is resolved on the announcement date. Consistent with this, we find that our measure decreases prior to the announcement and increases post announcement.

In a robustness exercise, we verify that options market one-sidedness is not related to contemporaneous and future stock liquidity and trading volume. This alleviates concerns that our results are driven by changes in liquidity of the underlying or increases in hedging demand driven by greater stock market volume.

Given that options market sidedness identifies informed trading it is likely that market makers respond to the presence of informed investors. We find that options market one-sidedness is associated with future higher option bid-ask spreads. Additionally, we find that a more one-sided options market predicts violations of put-call parity. These results are consistent with market makers gradually incorporating the information in the demand of informed traders and more generally with the perspective furthered by Garleanu, Pedersen and Poteshman (2009) that demand pressure in options markets should impact prices and price efficiency.

A possible alternative explanation of our results is that investors are not informed about the returns of the underlying, but about the volatility (see e.g., Back 1993, Ni, Pan and Poteshman 2008, Puhan 2014). Hence, it is important to distinguish whether the excess demand is coming from directional or volatility traders. To this end we develop a measure of volatility informed trading and find that including our measure of volatility informed demand does not qualitatively affect our previous results.

The contribution of this paper is threefold. First, this paper introduces the concept of market sidedness to the options market literature and examines its predictability and information content. Second, the measure of options market sidedness that we develop has a number of desirable features: i) OMS captures the part of option demand that is in excess of the demand associated with other trading motives. This solves the empirical challenge of separating informed demand from other motives of trade in the options markets; ii) the information content is volatility neutral, which is to say that the predictability associated with the measure is not due to volatility information;[5] iii) the measure is easy to calculate and uses only widely available and low frequency data, which means it is applicable to a large set of markets and for long time periods. It also does not require a structural model that signs trades as buyer or seller initiated. Third, by using our measure of market sidedness we document the presence of informed demand in option markets that is not driven by other trading motives or other potential sources of return predictability. In particular, our work complements Pan and Poteshman (2006) who document that put-to-call volume

[5]For example, implied volatilities or asymmetries in implied moments have been shown to predict returns (see e.g., Cremers and Weinbaum 2010, Xing, Zhang and Zhao 2010). However, these measures are not by construction or intention volatility neutral.

ratios only when computed from signed options volume from detailed quote records (for most markets not widely available) contain directional information data; moreover, OMS can also clearly identify the sign and the strength of the directional information and indicates when markets are driven by uninformed trading motives (high measure values). In contemporary work Johnson and So (2012) find only negative information in options trading using the option to stock volume ratio (O/S) by Roll, Schwartz and Subrahmanyam (2010) while we show that there is also substantial positive information in options trading. Moreover, they cannot differentiate between markets that are driven by uninformed motives of trade and options markets that exhibit asymmetric information. Cao, Chen and Griffin (2005) also provide evidence in support of informed trading but they focus exclusively on takeover events.

The rest of this paper is organized as follows. In Section 3.4, we develop our concept of options market sidedness. Section 2 details the data and investigates the sidedness of the options market around M&A announcements. Section 2.4 tests the relation of options market sidedness and future stock returns. Section 3.5 considers trading strategies that condition on options market sidedness. In Section 2.6, we study the links between informed option demand and stock market trading. Section 2.7 considers the impact of informed option demand on liquidity levels and pricing efficiency. Finally, Section 3.8 concludes the paper.

2.2 Measuring Options Market Sidedness

Our measures of option market sidedness uses the fact that informed traders are most likely to trade in high leverage options that consequently are the most information sensitive. Therefore, associated with an increase in informed trading, the demand (which is proxied for by changes in open interest) for those contracts should increase relative to contracts that are less information sensitive.

We define an OMS measure for positive (OMS^+) and negative (OMS^-) information trading, respectively. We compute the positive information measure OMS^+ as the correlation of the change in open interest of OTM call options and the change in open interest of ITM put options. More formally, the value of the positive signal measure OMS_t^+ is computed on each day t as

$$OMS_t^+ = \frac{\frac{1}{\tau}\sum_{s=t-\tau}^{t}\left(\Delta OI_{s,OTM}^{C} - \overline{\Delta OI}_{t-\tau:t,OTM}^{C}\right)\left(\Delta OI_{s,ITM}^{P} - \overline{\Delta OI}_{t-\tau:t,ITM}^{P}\right)}{\sqrt{\sigma^2_{\Delta OI^C_{t-\tau:t,OTM}}}\sqrt{\sigma^2_{\Delta OI^P_{t-\tau:t,ITM}}}}, \quad (2.2.1)$$

for a backward looking window of τ days.[6]

Analogously, in case of negative information trading, the OMS^- measure is the correlation of the change in open interest of OTM put options with the change in the open interest of ITM call options.

Intuitively, when either correlation is low then increases in demand for information sensitive (out-of-the-money) contracts are not accompanied by increases in demand in less sensitive (in-the-money) contracts. In the terminology of Sarkar and Schwartz (2009) the market is one-sided and is characterized by asymmetric information.[7] On the other hand when the correlation is high then an increase in demand of information sensitive contracts is also associated with an increase in less information sensitive contracts.[8]

Our measure is also able to capture when informed investors have a particularly strong signal. In such cases there will be a particularly large demand for OTM options and in equation (2.2.1) the deviation from the mean level of demand will be large and all other things being equal the correlation will take lower values.

There are two advantages of using a correlation over alternative measures such as a simple ratio, a difference in mean values or simple changes in open interest. First, the correlation is standardized by the variation of the variables (so in a simple sense we control

[6] In our analysis, we compute the time series of the daily OMS measures for each security, for a $\tau = 30$-day backward looking correlation between daily changes in open interest. The choice of this time window follows the idea that it would be rather counterintuitive to assume that most often options market informed trading happens at longer-term horizons (cf., Easley et al. 1998). However, we do not know ex ante when exactly informed traders trade. It would be implausible to expect that usually the informed traders buy options on only one day. Therefore we focus on a time horizon that spans approximately the temporal distance between two maturity dates to capture the gradual increase in informative excess demand in the options market. We have also tested a decreased or expanded correlation window size within a reasonable range of days (15 to 45 days), but our results remain qualitatively unchanged.

[7] Due to technical trading strategies, liquidity needs or hedging demand, there is always a certain natural level of demand and supply across contract types.

[8] An alternative measure would relate the open interest OTM calls to OTM puts, but this measure would not be able to distinguish the sign of the information.

for volatility). Second, the variation is benchmarked against its own mean, implying that we are considering above average deviations in open interest. Or put differently, we are considering whether above average excess demand in OTM options coincides with above average excess demand of ITM options.

We base our measure on changes in open interest since this arguably has a stronger connection with informed option demand. Table 2.1 illustrates the effect on volume and open interest of a transaction between Buyer A and Seller B.

Table 2.1: ΔOI **vs.** $Volume$**.** The table summarizes all possible four combinations for the opening and closing of option positions between some buyer A and some seller B. The column named ΔOI indicates the potential changes in the open interest related to the trading combination and their sign. The column $Volume$ reports whether there is a positive trading volume.

	Buyer A	Seller B	ΔOI	$Volume$
1:	buy to open	sell to open	> 0	> 0
2:	buy to close	sell to close	< 0	> 0
3:	buy to open	sell to close	$= 0$	> 0
4:	buy to close	sell to open	$= 0$	> 0

In case 1 buyer A wants to buy a contract to open a new position and seller B has to create a new position in order to cater to the demand, the open interest increases and there is positive trading volume. Alternatively, in case 2, if buyer A enters the options market to buy a contract to close a position, and seller B sells this contract, thereby closing a previously held position, there is a decrease of open interest along with positive option trading volume.

While both case 1 and case 2 result in a change in the open interest it is likely that case 1 is going to contain the most information. Intuitively, the demand from informed investors is going to result in the creation of new contracts and this is supported by the findings of Ni et al. (2008), Pan and Poteshman (2006), Muravyev (2013), Lakonishok et al. (2007), Bollen and Whaley (2004), Easley et al. (1998), Garleanu et al. (2009) or Chesney et al. (2011). Put differently, for case 2 to contain information this requires that the informed investor and the market maker to have open positions in this option, which is on average relatively unlikely given that the signal is truly informative.

Furthermore, in cases 3 and 4, we observe positive trading volume, however, since in both cases one party opens and another party closes a position, there is no change in the open interest even though we observe trading volume. This illustrates why using trading volume is different from considering excess option demand and arguably why it is a more noisy measure of informed demand.[9]

2.3 Data and Descriptive Analysis

In this section we describe the data selection, summarize the data and provide evidence about options market sidedness around M&A announcement dates.

2.3.1 Data and Summary Statistics

Our daily options market data consist of all American option contracts for all available US stocks at the intersection of OptionMetrics Ivy DB and CRSP stock market data described below.[10] The options have a standard settlement (i.e., per contract 100 shares of the underlying are delivered at exercise). The sample period is January 1996 until December 2009. We exclude option contracts with a maturity of more than 250 days and observations with no or zero open interest to exclude options without liquidity (cf., Driessen et al. 2009). We merge this data with the daily stock market data from the CRSP NYSE/AMEX/NASDAQ return files. Only securities from the merged CRSP and Compustat database are in the sample. We exclude stocks with a return history of less than 24 consecutive months. We exclude observations at the 99% and 1% level with respect to BM and we exclude stocks with a stock price below 1USD or with a return above 80% or below -80%.[11,12] After applying these filter rules, 4,155 firms remain in our final sample and 35,349 call and put contracts resulting in more than 5 million daily observations for each variable.

[9]The difference between changes in open interest and volume is also evident in the unconditional correlation of OTM option changes in open interest and trading volume, which is only 0.1 for call options and 0.08 for put options, respectively. Consistent with this, the unconditional correlation of the OMS measure computed with changes in open interest and an OMS measure computed with trading volume is very low and only 0.118 and 0.124 for OMS^+ and OMS^-, respectively. The low correlation between option order imbalances and option volume in Muravyev (2013) also highlights the noisiness of option volume as a measure of option demand.

[10]OptionMetrics Ivy DB is a comprehensive data set with information on the entire US equity options market.

[11]The annual book-to-market ratio on day t is given by the previous year's end-of-year book equity divided by the corresponding year's market equity (BM) (see Daniel and Titman 2006).

[12]Our results are robust to removing any of these cleaning rules.

We then sort all option contracts of each stock in moneyness categories in order to aggregate the option variables of interest for each moneyness group. Similar to e.g. Chakravarty et al. (2004), Lakonishok et al. (2007) or Xing et al. (2010) we define the moneyness range for options as the ratio of the strike price K and the stock price S (for call options $\frac{K}{S}$ and for put options $\frac{S}{K}$).[13] For OTM options the respective ratio is larger than 1.05 and for ITM options it is smaller than 0.95. Accordingly, ATM options have a moneyness range of 0.95–1.05. For the OTM part of our OMS measure we consider only those contracts that are OTM on at least 2 out of 5 days during the fourth week before the maturity date.[14]

After selecting options into moneyness categories we aggregate the daily open interest for each moneyness category, i.e., ITM Call, ITM Put, ATM Call, ATM Put, OTM Call, and OTM Put.[15] For each stock k we compute the median of the open interest of option contracts in a moneyness category.[16,17] The daily change in open interest is calculated separately for call and put options within a moneyness category and subsequently used to compute our measures of options market sidedness.

Table 3.1 provides summary statistics for the OMS^+ and OMS^-. The overall number of observations is roughly 5 million for OMS^+ and OMS^-.

OMS^+ and OMS^- are on average positively valued (0.43 and 0.46) and the 25% quantile is also positive (0.11 and 0.16), which is to be expected since directionally informed demand is neither permanent nor frequent; hence it would be surprising to observe a large fraction of negative OMS values.

As control variables we construct alternative information measures the daily option volume and option bid-ask spread. We aggregate the number of traded contracts ($VOL^j_{t,m}$) for each stock as the median of the volume for call and put option ($j = \{C, P\}$) separately

[13] To test the robustness of our results with respect to our moneyness definition we also compute the moneyness ratio as $ln\left(\frac{K}{F}/IV_{ATM}\sqrt{T}\right)$, where F is the futures price and IV_{ATM} is the implied volatility of ATM options of the respective stock. Our results qualitatively do not change if we use this ratio.

[14] We have also considered alternative OTM day selection rules up to two weeks before maturity and with more or less minimum OTM days; our results are qualitatively unchanged.

[15] The daily preliminary open interest is reported at the end of each trading day and the final official data is released on the following morning.

[16] We use the median in order to mitigate the impact of potential outliers.

[17] In what follows, we omit for reasons of simplicity the index k. Nevertheless, all measures and variables are computed for each single underlying stock.

Table 2.2: **Descriptive Statistics of Sample Variables.** The table provides summary descriptive statistics for sample variables across the full sample period from January 1996 until December 2009. The table reports the mean, the standard deviation (Std), the median, the 25 percent (Q25) and the 75 percent quantile (Q75) across all sample firms. OMS^+ and OMS^- are the options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). $BETA$ is the individual stock market beta, $SIZE$ is the logarithm of market equity. BM is the logarithm of the book-to-market ratio measured by book equity divided by, market equity using the fiscal year-end value preceding year. The realized volatility (RV) is in basis points and is defined as in Ni et al. (2008) as 10,000 times the difference of an underlying stock's intraday high and low prices divided by the closing stock price. MOM is the cumulative return over a 60 days backward looking window. STD is the average realized standard deviation obtained from the daily returns over a 60 days backward looking window. $SPREAD^C_{OTM}$ and $SPREAD^C_{ITM}$ are the median daily relative bid-ask spreads of call options that are OTM or ITM. $SPREAD^P_{OTM}$ and $SPREAD^P_{ITM}$ are the median daily relative bid-ask spreads of put options that are OTM or ITM. $SVOL^C_{OTM}$ and $SVOL^C_{ITM}$ denote the square root of the daily median call option trading volume that are OTM or ITM. $SVOL^P_{OTM}$ and $SVOL^P_{ITM}$ denote the square root of the daily median put option trading volume that are OTM or ITM. The descriptives for the OMS measure, the daily option spreads and option volume are formed using all days where the respective variable was nonzero.

	Mean	Std	Q25	Median	Q75	No. Obs.
OMS^+_t	0.423	0.398	0.114	0.473	0.751	5,015,363
OMS^-_t	0.461	0.397	0.158	0.526	0.795	5,396,556
$BETA$	1.206	0.418	0.842	1.095	1.442	7,011,930
$SIZE$	7.208	1.629	6.089	7.115	8.221	7,011,930
BM	0.784	5.784	0.256	0.446	0.745	7,011,930
RV	415.06	359.582	198.413	315.217	510.386	7,011,930
MOM	0.032	0.267	-0.091	0.0378	0.160	7,011,930
STD	0.0312	0.019	0.018	0.026	0.039	7,011,930
$SPREAD^C_{OTM}$	1.108	0.780	0.303	1.028	2.000	6,918,180
$SPREAD^C_{ITM}$	0.100	0.145	0.047	0.075	0.111	6,920,299
$SPREAD^P_{ITM}$	0.115	0.180	0.049	0.078	0.121	6,799,572
$SPREAD^P_{OTM}$	1.074	0.739	0.353	1.000	2.000	6,797,715
$SVOL^C_{OTM}$	4.423	4.558	1.871	3.162	5.292	6,918,180
$SVOL^C_{ITM}$	3.507	3.399	1.581	2.739	4.123	6,920,299
$SVOL^P_{ITM}$	3.741	4.429	1.581	2.739	4.472	6,799,572
$SVOL^P_{OTM}$	4.559	5.021	2.000	3.162	5.292	6,797,715

in each moneyness category m. Because the distribution of $VOL^j_{t,m}$ is right-skewed we use in our regressions $SVOL^j_{t,m}$, i.e., the square root of daily volume for call or put options.[18]

Similarly, we also control for bid-ask spreads. $SPREAD^j_{t,m}$ and $SPREAD^j_{t,m}$ denotes the median daily relative bid-ask spread of call or put options in different moneyness categories m.

Table 3.1 provides also summary statistics for option spreads and volume. The spread

[18]The square root of the volume is useful to normalize the variable.

size varies substantially with the moneyness ranges, the mean of the spread is roughly 1 for the OTM options ($SPREAD^C_{OTM}$, $SPREAD^P_{OTM}$) and roughly 0.1 for the ITM options ($SPREAD^C_{ITM}$, $SPREAD^P_{ITM}$). This is in accordance with the well-known fact that it is more expensive to trade in OTM options. Nevertheless, OTM options are usually the most actively traded type of options, which is also the case in our sample. The normalized options trading volume is relatively higher for OTM options ($SVOL^C_{OTM}$, $SVOL^P_{OTM}$). However, the difference between the trading volume of OTM and ITM options is not extremely large, for instance for call options $SVOL^C_{OTM}$ is 4.4 and $SVOL^C_{ITM}$ is 3.5. This is important since we correlate the ITM options with the OTM options, in order to capture the information trading related excess demand. If the level of trading activities in ITM options was extremely lower than for OTM options, it would be difficult to identify information in OTM excess option demand.

Other variables that we extract from CRSP are the closing price, high and low prices, shares outstanding and the volume as the total number of traded shares of stock. We also use a proxy for the underlying's daily realized volatility, which we define as in Ni et al. (2008) as 10,000 times the difference of the underlying stock's intraday high and low prices divided by the closing stock price (RV). Market equity is defined as the price of a stock on day t multiplied by the shares outstanding. The logarithm of market equity is used to measure firm size ($SIZE$). We compute momentum (MOM) as the 60 days backward looking cumulative return and long-term volatility (STD) as the square root of the averaged cumulative squared returns.

Also from CRSP we obtain a value weighted NYSE/AMEX index with dividends as a proxy for monthly market returns. From all returns of the individual stocks and the market index we subtract the average one month risk free rate from the Fama risk free rates file as provided by CRSP. We obtain monthly market betas as in Easley et al. (2002) and denote the individual stock market beta as $BETA$. In the daily cross-sectional regressions we include the stock's previous month's market portfolio betas to control for the single stock's market risk exposure. Descriptive statistics for $BETA$, $SIZE$, BM, RV, MOM and STD are in Table 3.1. As a proxy for stock market illiquidity, we compute the Amihud (2002) illiquidity measure in basis points as $ILLIQ_{Amihud} = 1 \times 10^{10} * |RET|)/Volume$, where $Volume$ is the daily trading volume of a stock. We extract annual fiscal year-end book equity values from the COMPUSTAT data base.

Earnings announcement dates (EAD) are obtained from the I/B/E/S Database.

2.3.2 Information in Option Demand around High Information Events

In this section, we use M&A announcements to validate that our measure captures informed demand. Prior to M&A announcements there is arguably a significant amount of asymmetric information that is resolved at announcement. This implies that we expect our measure to decrease in the pre-announcement period (as there is an increase in informed demand) and post-announcement we expect this decrease to be reversed. To ensure that our measure captures directional information we pair OMS^+ (OMS^-) with events with positive (negative) announcement day returns.

The M&A data is from the SDC Platinum database and we follow Schwert (1996) in defining the announcement date as the first day when an official bid becomes known. We exclude firms that have received another bid in the same year. We calculate the cumulative change in OMS^+ and OMS^- from 7 days before the announcement day $t = 0$. Figure 2.1 describes the change in the OMS measures over this period in the positive (upper subfigure) and negative (lower subfigure) informed demand case.[19] The plot of the cumulative changes for the M&A dates is marked in green and with dots. As a benchmark we also plot (in red and with triangles) the average OMS measure changes of firms not making announcement. The figure illustrates that our as predicted, directly before the M&A announcement, i.e., on the evening before the announcement day, we observe that the cumulative change in OMS^+ exhibits 27 times lower values than the benchmark case and for OMS^- it is more than 30 times lower.

Moreover, there is a significant reincrease in the measures ex post the M&A announcement, which reflects that once the news become public and options markets become more two-sided.

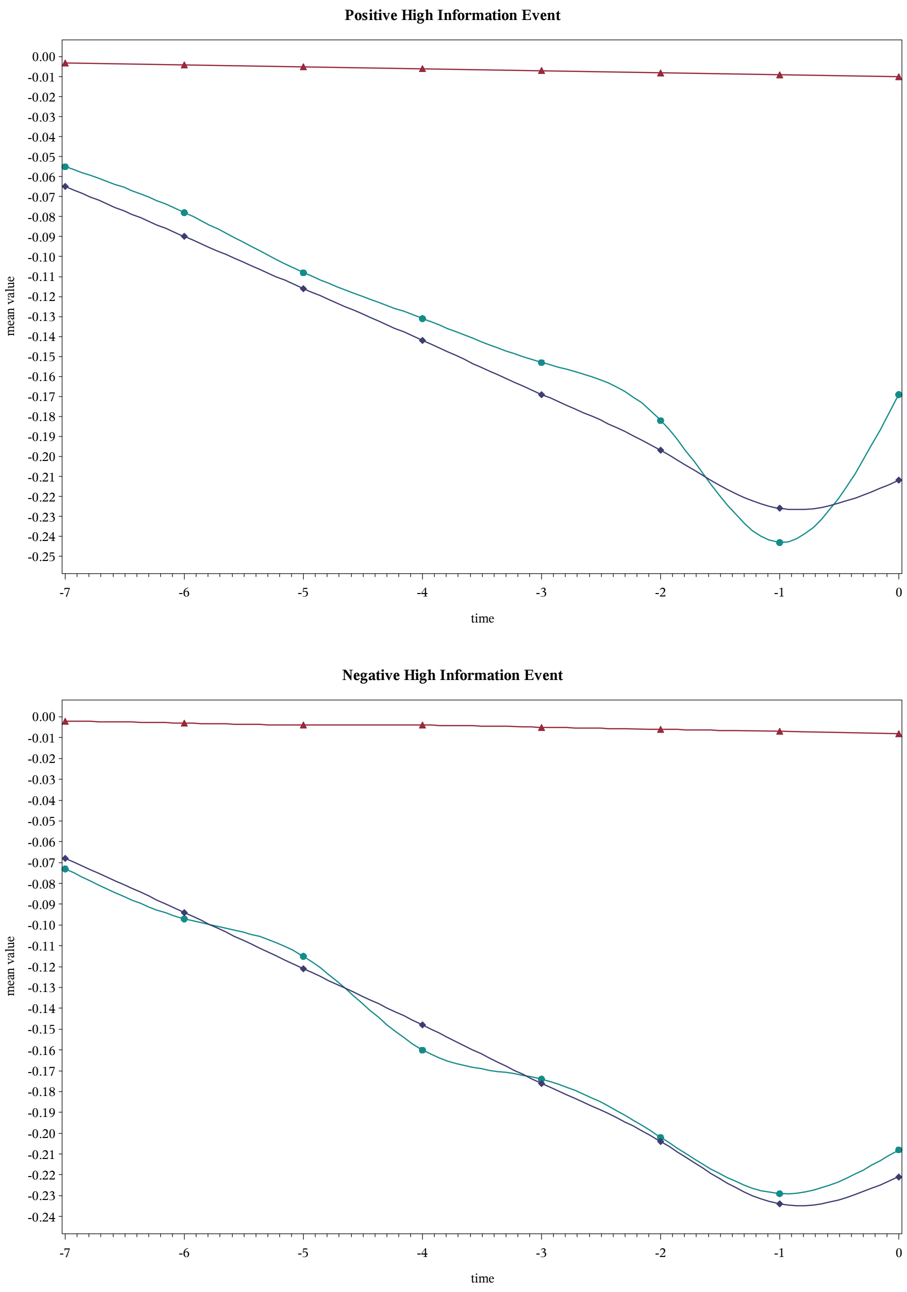
To verify the robustness of the M&A announcement date results, we also consider days

[19]We choose a 7-day window before the high information date as a reasonable time window before a high information event where we would expect the major demand of investors with private information related to the event. Given the high information content of the event, it is unlikely that investors obtain the directional signal a long time before the event. However, our results do not qualitatively change if we extend the time window within a sensible range.

with large return movements, which arguably are also events of high information.[20] The plot of the cumulative OMS measure changes around the extreme return dates is marked in blue and with diamonds and confirms the patterns that we find for the M&A announcement dates.

[20]In the positive information case we define high return events as days where the return is above the average daily return within the subsample of days with positive returns and in the negative information case we consider days where the return is below the average return on a negative return day.

Figure 2.1: **Informed Option Demand and High Information Events.** In this figure, we compare the mean values of the cumulative change in the OMS measures before M&A announcements and days with large return movements as events of high information revelation. We define positive (negative) information large return days as days when the return is above (below) the mean return of all days with positive (negative) returns. As a control group we use the full sample average. The high information date is defined as $t = 0$. We plot the cumulative changes of the OMS^+ and OMS^- measure for the 7 days before high information events. The plot of the cumulative changes for the full sample is marked in red and with triangles. The plot of the cumulative changes for the M&A dates is marked in green and with dots. The plot of the cumulative changes for the extreme return dates is marked in blue and with diamonds. The upper subfigure plots the different variables for the positive information case. The lower subfigure plots the different variables for the negative information case. The full sample period is January 1996 to December 2009.



2.4 Option Market Sidedness and Future Stock Returns

In this section, we examine the relationship between options market sidedness and future stock returns. In particular, we investigate whether an increase in options market one-sidedness, i.e., lower OMS^+ (OMS^-) values, predicts higher (lower) stock returns.

2.4.1 Option Market Sidedness Sorted Stock Portfolio Returns

Panel A of Table 2.3 reports daily mean stock excess returns for equity portfolios that are sorted into different groups according to the firm individual OMS measure value. The OMS measure is a correlation and thus it takes values on a scale from -1 to +1. To form stock portfolio groups, we set the portfolio break points at 0.2 interval steps of the OMS^+_{t-1} and OMS^-_{t-1} measure, respectively, resulting in 10 portfolios. We compute the mean excess returns at day t of these 10 portfolios across our sample firms.[21] In Panel A of Table 2.3 we observe that the OMS groups vary in their size from roughly 25,000 observations to more than 1 million. The relatively smaller (but still quite sizeable) number of very low OMS is intuitive since negative OMS values reflect option demand induced by extremely strong information signals. It is also more likely that private information trading is reflected in a gradual decrease of the measure.

Consistent with option market one-sidedness being an indicator of asymmetric information, we find for lower values of the OMS measure (i.e., the options demand is more one-sided) higher future equity portfolio returns if we sort according to the positive information measure and lower future returns for the negative information case. The average daily return difference (0.12 for OMS^+ and -0.11 for OMS^-) between the portfolio that is associated with the lowest OMS values (Low) and the portfolio of stocks with the highest OMS values (High) shows that the average daily return spread from low to high OMS values is highly significantly different from zero and exhibits also the right sign. If we compare the lowest portfolio (1) with portfolio (9) the economic magnitude of the return difference is even larger.

[21] We use stock returns that are in excess of the risk-free rate. If we risk-adjust them with respect to the Fama-French and Carhart factors, the quality of the results remains unchanged.

Table 2.3: **Single and Double Sorted Portfolio Excess Returns.** The table reports daily mean excess returns at time t for OMS_{t-1} measure grouped portfolios (Panel A). OMS^{+}_{t-1} and OMS^{-}_{t-1} are the options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). We construct OMS^{+}_{t-1} and OMS^{-}_{t-1} measure groups of the underlying stocks and compute the contemporaneous daily mean excess return of these portfolios. Portfolio returns are in percentages. The OMS measure takes values on a scale from -1 to +1, thus we form 10 portfolios where in each portfolio the stocks' OMS values span a 0.2 range. In the last column we compute the average daily return difference between the lowest OMS portfolio and the highest OMS portfolio. *** indicate a significance of the return difference at a 1% level, ** at a 5% level and * at a 10% level. Panel B reports the average returns for portfolios sorted according to $VolOMS^{+}$ and $VolOMS^{-}$, i.e., options market sidedness measures that are computed with trading volume instead of changes in open interest as in the original OMS measure. N_{PF} is the number of observations in each portfolio. The sample period is January 1996 to December 2009.

Panel A: OMS-Sorted Portfolio Returns in Percent											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	Low - High
	Low					OMS^{+}_{t-1}				High	L-H: OMS^{+}_{t-1}
Daily $\overline{Ret}_t$ (%)	0.203	0.16	0.098	0.079	0.058	0.029	-0.034	-0.046	-0.030	0.073	0.12***
N_{PF}	34,722	46,398	73,500	119,622	475,600	764,753	679,025	812,852	926,336	1,013,504	
	Low					OMS^{-}_{t-1}				High	L-H: OMS^{-}_{t-1}
Daily $\overline{Ret}_t$ (%)	-0.126	-0.082	-0.064	0.022	0.044	0.075	0.123	0.122	0.092	-0.013	-0.112***
N_{PF}	33,309	43,050	69,471	112,235	472,177	737,474	683,548	848,467	1,029,269	1,303,315	
Panel B: $VolOMS$-Sorted Portfolio Returns in Percent											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	Low - High
	Low					$VolOMS^{+}_{t-1}$				High	L-H: $VolOMS^{+}_{t-1}$
Daily $\overline{Ret}_t$ (%)	0.2780	0.261	0.294	0.302	0.120	0.074	0.034	-0.001	-0.041	-0.043	0.212
N_{PF}	183	74	383	6,746	696,697	320,299	257,165	225,322	206,803	230,158	
	Low					$VolOMS^{-}_{t-1}$				High	L-H: $VolOMS^{-}_{t-1}$
Daily $\overline{Ret}_t$ (%)	2.288	0.713	-0.003	-0.209	-0.026	0.009	0.044	0.083	0.102	0.085	1.120***
N_{PF}	162	56	429	5,723	770,477	339,921	280,075	253,307	226,857	266,518	

It is evident from Table 2.3 that the relation between the lagged OMS measures and stock returns exhibits a nonlinear pattern. The returns decrease (increase) nonlinearly with an increase in OMS^{+}_{t-1} (OMS^{-}_{t-1}). This return pattern reflects substantial price adjustments for extremely low OMS values and indicates that the OMS measure is able to indicate when the information signal is strong, informed investors trade aggressively and take larger positions. Analogously, these findings hold but with reversed signs for the equity portfolio returns of the OMS^{-}_{t-1} sorted portfolios. However, even with this reincrease in returns, the return spreads between the lowest and highest portfolios are still highly significantly different from zero.

In Panel B of Table 2.3, we compute an OMS measure using option trading volume ($VolOMS^{+}$ and $VolOMS^{-}$) instead of changes in open interest. The results show that a volume based OMS measure is not successful in identifying when markets are driven by asymmetric information and when by heterogenous beliefs. Sorting according to $VolOMS^{+}$ results in an insignificant return spread between the Low and the High $VolOMS$ group and and for $VolOMS^{-}$ the spread is significant but with the wrong sign (the returns in the Low portfolio have to be lower than the returns in the High portfolio). Moreover, we observe that almost all $VolOMS$ value observations are ≥ 0, which further supports the notion that for trading volume it is rather difficult to differentiate between informed demand and other trading motives.

2.4.2 Cross-Sectional Stock Return Predictions

We use Fama and MacBeth (1973) (FMB) regressions to test the relation of future individual stock returns and the directional OMS measure.[22] The empirical specification reads as,

$$RET_t = \beta_0 + \beta_1 OMS^{+}_{t-1} + \beta_2 OMS^{-}_{t-1} + \mathbf{bC}_t + \epsilon_t, \tag{2.4.1}$$

where RET_t is the daily stock return in excess of the risk free rate.[23] β_0, β_1 and β_2 denote the coefficients of the intercept, the OMS^{+}_{t-1} and the OMS^{-}_{t-1} measure at day $t-1$.

[22] We choose daily windows for the entire empirical part. Obviously, informative signals can persist intradaily, for one or two days or for longer periods, depending on the nature of the signal. Most often, the information asymmetry occurs at a daily or intradaily level, thus the daily windows that we use are a viable choice (see also Pan and Poteshman 2006).

[23] If we risk adjust the returns with regard to the Fama-French and Carhart factors, the quality of the results remains unchanged.

Further, we include in (2.4.1) $\mathbf{C_t}$, which is a vector of control variables such as firm size, book-to-market ratio, market returns, lagged stock returns, long-term past stock returns, long-term past stock return volatility and option volume. The corresponding coefficient vector is $\mathbf{b}$.

We conjecture a negative (positive) sign for β_1 (β_2), reflecting that OMS^+_{t-1} (OMS^-_{t-1}) takes lower values due to the positively (negatively) informed demand and predicts higher (lower) returns in the future.

Table 2.4 reports the main FMB-regression results with stock returns as dependent variable.[24] We use percentage returns in the regressions and can therefore interpret the estimated coefficients directly as a percentage change in returns the day after e.g. the directional OMS measure drops from zero to minus one.

In column (I), we validate the predictive power of the directional OMS measure, firstly without including any of the control variables. The coefficient of the OMS^+_{t-1} measure is negative and statistically significant. This supports our hypothesis that OTM call option excess demand indicates positive information trading. Our results imply that a drop of the OMS^+_{t-1} measure from zero to minus one is associated with an increase of the returns on the next day by 16 basis points (or an annualized 49% increase in returns). If we compute the standardized coefficient we obtain for a one standard deviation decrease in OMS^+ a 6.4 basis points increase in the next day's return (or an annualized 16%).

The coefficient of the OMS^-_{t-1} measure is as expected positive and significant. The decrease in the return on the next day that is implied by an OMS^- measure change from zero to minus one is 15 basis points or 6.1 basis points for the standardized coefficient.

The t-statistics of our measures are smaller than in Pan and Poteshman (2006) (who use private data) but much larger than those generally found in this literature.

In all columns we include squared terms of our OMS measures. The squared OMS measure coefficients always exhibit the opposite sign to the respective original measure indicating that a negative change in the directional OMS that is close to minus one, i.e.,

[24] To save space we omit the results for the stock related control variables in the table. They are available on request.

the information is stronger and options market are more one-sidedness, is associated with a relatively larger return movement than a negative change in OMS close to zero.[25]

In column (II) we also add the contemporaneous OMS^+ and OMS^- measures in order to validate the predictive power of the lagged OMS variables. The testable prediction for this specification is that the contemporaneous term exhibits the opposite coefficient with respect to the coefficients of the lagged OMS measures since at time t the information becomes public and options markets exhibit less information asymmetry, i.e., the OMS measures takes higher values. Furthermore, the results for the lagged coefficients should qualitatively not be affected by including the contemporaneous term. This is exactly what we find.

In column (III), we control in addition for various other variables related to market risk, firm characteristics, liquidity and volatility. Our results are not affected by these controls.

Our OMS measure has two key components. First, the measure is based on changes in open interest to capture demand. In Section 2.4.1, Table 2.3 we show that performs better than volume as informed demand indicator. Second, by relating the demand for information sensitive contracts to insensitive contracts the measure separates informed demand from other trading motives. Therefore, we focus now on verifying that our measure of option market sidedness is superior to other potential measures that we could compute from changes in open interest.

In column (IV) we start with running a horse-race between the call-to-put-ratio ($CP - RATIO$), which we compute for each stock as the ratio of daily changes in open interest in call and in put option contracts minus one. As expected, we find that high values of the $CP - RATIO$ indicate bullish sentiment and high future returns. However, including the $CP - RATIO$ does not change our findings concerning the OMS measures and although statistically significant the statistical and economic significance of the CP ratio is lower.[26] In terms of economic significance, the standardized coefficient of the $CP - RATIO$ is only

[25]We have also tested whether our results still hold if we run the above daily regressions for each year in our sample separately. We find that the results are in almost all years qualitatively the same as for the whole sample.

[26]The unconditional correlation between the $CP - RATIO$ and the OMS measures is -0.02 for the OMS^+ and 0.002 for the OMS^- measure, respectively. If we construct the ratio using trading volume, the unconditional correlation between the ratio and the OMS variables is virtually zero.

one third as large as the OMS measures (i.e., 2 basis points vs. 6 basis points on a daily basis).[27,28]

In column (V), we include two alternative open interest based variables, $\overline{\Delta OI}^{C}_{OTM,t-1}$ and $\overline{\Delta OI}^{P}_{OTM,t-1}$. The variables are the means of the changes in the open interest of OTM call and put options in a 30-day rolling window. The results show that the simple average level effects of both excess demand variables have weak statistical and economical predictive power (standardizing the coefficients yields a change in the next day's returns of 1.8 (-3) bps for a one standard deviation change in $\overline{\Delta OI}^{C}_{OTM,t-1}$ ($\overline{\Delta OI}^{P}_{OTM,t-1}$)). Including these variables does also not affect the coefficients of the OMS variables.[29] Thus, basic levels are not sufficient, illustrating that relating OTM and ITM contracts is necessary to differentiate between different trading motives that might change the open interest.

In column (VI) we add the difference between $\overline{\Delta OI}^{C}_{OTM,t-1}$ and $\overline{\Delta OI}^{P}_{OTM,t-1}$, which is another alternative open interest based measure. Intuitively, the difference in both means might become larger in case of positive informed trading and should exhibit large negative values in case of negative information trading, yielding a positive regression coefficient. However, the coefficient is negative, which indicates that this measure fails completely to differentiate between changes in the open interest due to uninformed or informed reasons.

[27] Using alternatively for instance the simple call open interest, divided by the simple put open interest, does not affect our results. Using a ratio of standardized changes in open interest does also qualitatively not affect our results. All results are available on request.

[28] In unreported results, we include, as a control for market risk premia related option trading as explanation to the patterns that we find. More specifically, we regress the individual stock returns on directional OMS measures for positive and negative information trading at the index level (S&P500 equity index options). Since it is very unlikely that informed traders exploit directional signals at the index level, a significant negative (positive) coefficient for the positive (negative) information measure on the index level in the return regressions would indicate that OMS also picks up market risk premia (e.g., Puhan 2014, Pan and Poteshman 2006). However, we find only insignificant results for the coefficient of the index OMS measures.

[29] The unconditional correlation between the $\overline{\Delta OI}^{C}_{OTM,t-1}$ and OMS^{+} is -0.04 and between $\overline{\Delta OI}^{P}_{OTM,t-1}$ and OMS^{-} the correlation is -0.06. If we construct the 30 day averages with levels or changes in trading volume, the unconditional correlations are virtually zero.

Table 2.4: **FMB-Regression Results for Daily Individual Stock Excess Returns on the Directional OMS Measures and Controls.** The table provides daily FMB-regression results of individual stock's excess returns (RET) on the directional OMS measures as well as on control variables. Returns are in percentages. OMS^{+}_{t-1} and OMS^{-}_{t-1} are the lagged options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). $OMS^{2,+}_{t-1}$ and $OMS^{2,-}_{t-1}$ are the corresponding quadratic terms. $SVOL^{C}_{OTM}$ and $SVOL^{C}_{ITM}$ is the square root of the daily median call option trading volume that are OTM or ITM. $SVOL^{P}_{OTM}$ and $SVOL^{P}_{ITM}$ is the square root of the daily median put option trading volume that are OTM or ITM. $CP-RATIO$ is a daily ratio of the aggregated changes in open interest for call options divided by the aggregated changes in the open interest for put options minus one. $\overline{\Delta OI}^{C}_{OTM,t-1}$ is a 30-day rolling window mean of the change in open interest in OTM call options. $\overline{\Delta OI}^{P}_{OTM,t-1}$ is a 30-day rolling window mean of the change in open interest in OTM put options. EAD is a dummy that is one if the day is an earnings announcement day and zero otherwise. The results for the stock related control variables (*Stock Controls*) are omitted. *Stock Controls* includes: EAD, market beta ($BETA$), size ($SIZE$), book-to-market (BM), momentum (MOM), volatility (STD). The definitions of the control variables are summarized in Appendix 1. Newey-West robust t-statistics are in parentheses (20 lags). *** indicate a significance at a 1% level, ** at a 5% level and * at a 10% level. The R^2 is the average cross-sectional adjusted R^2. *No. Firms* is the overall number of stocks in the regression. The sample period is January 1996 to December 2009.

RET_t	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Constant	0.045	0.048*	-0.087	-0.122**	-0.095*	-0.086	-0.051	-0.05
	(1.59)	(1.67)	(-1.47)	(-1.97)	(-1.66)	(-1.46)	(-0.85)	(-0.84)
OMS^{+}_{t-1}	-0.166***	-0.502***	-0.169***	-0.162***	-0.169***	-0.169***	-0.158***	-0.169***
	(-11.55)	(-8.08)	(-11.57)	(-10.13)	(-11.68)	(-11.66)	(-12.11)	(-11.49)
OMS^{-}_{t-1}	0.167***	0.593***	0.116***	0.121***	0.115***	0.116***	0.136***	0.136***
	(10.72)	(9.62)	(7.18)	(7.46)	(7.1)	(7.15)	(9.09)	(7.45)
$OMS^{2,+}_{t-1}$	0.215***	0.21***	0.195***	0.184***	0.194***	0.194***	0.174***	0.195***
	(13.34)	(13.12)	(13.54)	(11.93)	(13.58)	(13.5)	(12.55)	(13.43)
$OMS^{2,-}_{t-1}$	-0.255***	-0.254***	-0.227***	-0.239***	-0.224***	-0.226***	-0.223***	-0.225***
	(-16.22)	(-16.16)	(-14.12)	(-14.45)	(-13.92)	(-14.02)	(-14.42)	(-14.15)
OMS^{+}_{t}		0.344***						
		(6.06)						
OMS^{-}_{t}		-0.435***						
		(-7.6)						
$SVOL^{C}_{OTM}$			0.078***	0.075***	0.080***	0.079***	0.067***	0.077***
			(21.39)	(21.11)	(21.51)	(21.7)	(19.62)	(21.3)
$SVOL^{C}_{ITM}$			-0.027***	-0.027***	-0.028***	-0.027***	-0.017***	-0.077***
			(-4.99)	(-4.97)	(-5.03)	(-4.91)	(-3.29)	(-4.84)
$SVOL^{P}_{ITM}$			0.082***	0.08***	0.084***	0.083***	0.062***	0.081***
			(13.60)	(13.29)	(13.45)	(13.51)	(9.82)	(13.80)
$SVOL^{P}_{OTM}$			-0.15***	-0.147***	-0.152***	-0.152***	-0.138***	-0.135***
			(-28.00)	(-27.21)	(-28.56)	(-28.45)	(-26.20)	(-28.09)
$CP-RATIO$				0.001***				
				(3.94)				
$\overline{\Delta OI}^{C}_{OTM,t-1}$					0.000*			
					(1.68)			
$\overline{\Delta OI}^{P}_{OTM,t-1}$					-0.001***			
					(-6.70)			
$\left(\overline{\Delta OI}^{C}_{OTM,t-1} - \overline{\Delta OI}^{P}_{OTM,t-1}\right)$						-0.001***		
						(-5.61)		
OMS^{σ}_{t-1}							0.007	
							(1.47)	
$OMS^{C}_{t-1} \cdot EAD_t$								3.56
								(1.00)
$OMS^{P}_{t-1} \cdot EAD_t$								-1.496
								(-1.07)
Stock Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.003	0.006	0.112	0.119	0.113	0.113	0.128	0.132
No. Firms	4,155	4,155	4,155	4,155	4,155	4,155	4,155	4,155

A potential alternative explanation of our results could be that investors might have information about the volatility of future returns (RV).[30] We control for volatility trading by including a measure of volatility informed demand that we call OMS^{σ}. We measure the option demand of the volatility traders by selecting all closest to maturity ATM call and put option pairs that could be part of a straddle strategy and correlate their change in open interest for a 30-day backward looking window. More formally the measure reads as $OMS^{\sigma} = corr(\Delta OI^{C}_{ATM}, \Delta OI^{P}_{ATM})$, where ΔOI^{C}_{ATM} denote the changes in open interest of ATM call options and ΔOI^{P}_{ATM} the changes in open interest of ATM put options, respectively.[31] This measure of volatility informed option demand takes higher values whenever the open interest of both sides of the ATM option pair exhibits a stronger comovement, indicating volatility information related trading.

In Appendix 2 we verify that OMS^{σ} is indeed informative about future stock price volatility following Ni et al. (2008); we also show that before earnings announcement dates, which are known to be preceded by two-sided stock markets (Sarkar and Schwartz 2009) and followed by an increase in volatility (e.g., Ni et al. 2008, Beaver 1968), the predictive power of OMS^{σ} for future RV increases. In Appendix 2 we also show that OMS^{+} and OMS^{-} have no predictive power for future RV neither in normal times nor before earnings announcement dates.

We start by adding in column (VII) of Table 2.4 the OMS^{σ} measure. OMS^{σ} does not significantly predict stock returns. Furthermore, the results for the directional OMS measures are unaffected by including OMS^{σ}, showing that the predictive power of OMS^{+} and OMS^{-} is not associated with volatility informed trading.

Finally in column (VIII), we control for earnings announcement dates, as times of heterogenous beliefs and an increased future volatility, by interacting the OMS measure with

[30] Previous work of e.g. Back (1993), Ni et al. (2008) and Puhan (2014) show that the options market contains information on the future volatility of stock or index returns.

[31] Since the option Vega is greatest for at-the-money (ATM) options and volatility traders do not know the direction of the future stock return movement, we make the common assumption that volatility informed traders take straddle positions in ATM options in order to exploit their information (cf., Ni et al. 2008). Buying a straddle implies the creation of a new long position in an ATM call and put option with the same strike price and the same expiration date. Consequently, volatility informed trading results in a significant increase in changes in open interest for both call ATM option contracts that is strongly associated with the changes in open interest in ATM put options with the same maturity and strike price. This is also in line with findings from a private data set in Ni et al. (2008).

a dummy (EAD) that is equal to 1 if the date is an announcement date. If the predictive power of the measure for stock returns is indeed due to directional information trading, the predictive power should not increase before an earnings announcement day. Consistent with this, we find that $OMS^{+} \cdot EAD$ and $OMS^{-} \cdot EAD$ exhibit insignificant coefficients and the results for the non-interacted OMS terms remain unaffected. This supports that OMS^{+} and OMS^{-} indeed capture directional information.

In order to examine more closely the information content of option demand for future stock returns, we investigate next, similar to Pan and Poteshman (2006), the predictability horizon of the OMS measure. If our measures indeed pick up persistent patterns of directional information in option demand, we would expect the predictability to persist for several days and not to revert too quickly. So we extend the predictability horizon of OMS^{+} and OMS^{-} respectively up to 20 trading days. Figure 2.2 plots the slope coefficients of OMS^{+} on the left-hand side and the slope coefficients of OMS^{-} on the right-hand side. The dashed lines are the 95% confidence-intervals.

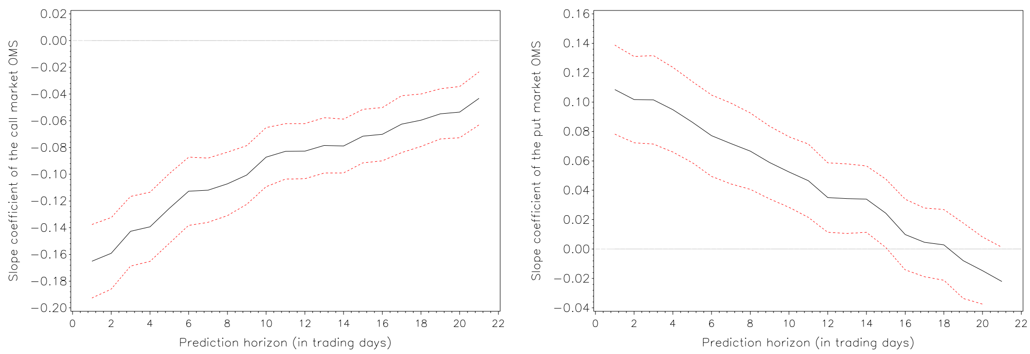
The plots show that the predictability is robust and relatively strong during the first three weeks in the positive information case and during the first two weeks in the negative information case. Subsequently, the predictability of OMS^{+} and OMS^{-} decays further and looses its economical and statistical significance. These results provide strong support for our hypothesis that option market one-sidedness indicates directional informed trading.

In 3 we investigate the information flows between the options market sidedness measures and stock returns. We test in a trivariate VAR system whether stock price changes Granger cause options market one- or two-sidedness and vice versa. We find that the information in the OMS measures is first reflected in the options market and moves only slowly into the stock market, which is consistent with the persistent predictive power of the OMS measures. Our analysis also reveals that stock market news trigger options market two-sidedness, i.e., heterogeneous beliefs.

Figure 2.2: **Predictability Horizon of the OMS Measure for Future Stock Returns.** In order to obtain the plotted time series, we run daily FMB-regressions of the following form

$$RET_t = \beta_0 + \beta_1 OMS^{+}_{t-i} + \beta_2 OMS^{2,+}_{t-i} + \beta_3 OMS^{-}_{t-i} + \beta_4 OMS^{2,-}_{t-i} + \mathbf{bC_t} + \epsilon_t,$$

where $i = \{1, 2, \ldots 20\}$. That is, we regress excess stock returns in percent at time t on the $t-i$ lag of the positive and negative information OMS measure (OMS^{j}_{t-i} with $j = \{+, -\}$) and the $t-i$ lag of the respective quadratic term ($OMS^{2,j}_{t-i}$). The vector of control variables (C_t) is as in the main regression in (2.4.1). The left figure plots the slope coefficient of OMS^{+} measure. The right figure plots the slope coefficient of OMS^{-} measure. The dashed lines are the 95% confidence intervals. The sample period is January 1996 to December 2009.



2.4.3 Sorts on Firm Characteristics

In the literature on stock and options market informed trading, several firm characteristics such as size are associated with an increased probability of informed trading in the options market. For instance, Easley et al. (1998) show that informed traders more likely trade in the options market if the underlying is smaller and less liquid and Ni et al. (2008) show that this is the case for higher volatility stocks.

In order to study the cross-sectional implications of excess option demand, we build quartile portfolios of stocks that are sorted according to the size or volatility of a firm at the end of the previous year. Then, we run the regression in (2.4.1) for each quartile portfolio.[32] The expected signs of the coefficients for the OMS measures are as in the above for regression model (2.4.1), however, we expect the absolute size of the coefficient to be larger for smaller and for higher volatility firms.

The regression results for portfolios sorted according to a firm's size or volatility are reported in Table 2.5. As in the previous regressions we control for several other factors such as past cumulated returns, lagged return, past standard deviation of the stock returns, option volume or market risk sensitivity.

In the left part of Table 2.5, the coefficients of the call and put options market sidedness measure (OMS^{+}_{t-1} and OMS^{-}_{t-1}) are as expected significantly negative and positive, respectively. In line with the predictions from Easley et al. (1998) there is a stronger relationship of private information trading and stock returns for smaller firms.

In the right part of Table 2.5, we consider cross-sectional regressions of the excess returns of quartile portfolios that are sorted according to the yearly return standard deviation. The coefficients of the OMS measure clearly increase in absolute terms with an increasing stock return volatility. These results confirm that informed traders are more likely to trade in higher volatility stocks.

Furthermore, we observe that in both sorting exercises, the results for the other portfolios, i.e., larger and less volatile firms, still remain significant, indicating that the predictive

[32] We also ran regressions for stock trading volume sorted quartile portfolio excess returns. However, the intuition for this sorting variable and the regression results are very similar to the size sorted portfolios. Therefore, we do not report them for reasons of brevity. They are available on request.

power of the OMS measures not restricted to small or highly volatile firms.[33]

[33] Another indication for the broad scope of the OMS measures is that excluding the observations in the lowest option volume quantile also does not change our results.

Table 2.5: **FMB-Regression Results for Size and Standard Deviation Sorted Quartile Portfolio Excess Returns on the OMS Measure and Controls.** The table provides daily FMB-regression results of excess returns (RET) of size ($SIZE$) and standard deviation (STD) sorted quartile portfolios on several control variables. The sorting variable $SIZE$ is the logarithm of market equity using the year-end value and STD is the yearly return standard deviation. Returns are in percentages. OMS^{+}_{t-1} and OMS^{-}_{t-1} are the options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). $OMS^{2,+}_{t-1}$ and $OMS^{2,-}_{t-1}$ are the corresponding quadratic terms. The other regressors are market beta ($BETA$), size ($SIZE$), book-to-market (BM), lagged returns (RET_{t-1}), momentum (MOM), volatility (STD). The definitions of the control variables are summarized in Appendix 1. Newey-West robust t-statistics are in parentheses (20 lags). *** indicate a significance at a 1% level, ** at a 5% level and * at a 10% level. The R^2 is the average cross-sectional adjusted R^2. The overall number of stocks in the regression is 4,155. The sample period is January 1996 to December 2009.

	Size Sorted Quartiles				**Volatility Sorted Quartiles**			
	Low	$SIZE$		High	Low	STD		High
$Constant$	-0.036	-0.041	-0.028	-0.016	-0.036	-0.027	-0.056	-0.203***
	(-0.97)	(-1.36)	(-1.02)	(-0.58)	(-1.26)	(-0.80)	(-1.41)	(-3.01)
OMS^{+}_{t-1}	-0.255***	-0.202***	-0.153***	-0.119***	-0.068***	-0.133***	-0.203***	-0.316***
	(-5.66)	(-7.76)	(-8.80)	(-9.07)	(-5.48)	(-6.52)	(-9.33)	(-8.75)
OMS^{-}_{t-1}	0.107***	0.116***	0.128***	0.116***	0.065***	0.12***	0.13***	0.156***
	(2.74)	(4.05)	(6.16)	(7.25)	(4.81)	(7.00)	(4.81)	(3.96)
$OMS^{2,+}_{t-1}$	0.348***	0.235***	0.192***	0.141***	0.096***	0.166***	0.228***	0.379***
	(7.43)	(7.74)	(10.23)	(9.06)	(7.90)	(7.95)	(9.28)	(9.04)
$OMS^{2,-}_{t-1}$	-0.234***	-0.231***	-0.222***	-0.17***	-0.113***	-0.192***	-0.248***	-0.303***
	(-5.77)	(-8.36)	(-10.24)	(-9.19)	(-9.02)	(-11.28)	(-9.91)	(-6.95)
$BETA$	-0.035**	-0.023	-0.04***	-0.054***	-0.004	-0.009	-0.008	-0.013
	(-2.12)	(-1.63)	(-2.65)	(-3.49)	(-0.27)	(-0.72)	(-0.58)	(-0.74)
$SIZE$					0.004*	0.005*	0.013***	0.04***
					(1.86)	(1.76)	(3.08)	(5.90)
BM	0.01	0.006	0.009**	0.011**	0.004*	0.004	0.008	0.026*
	(1.09)	(1.15)	(2.47)	(2.33)	(1.82)	(1.02)	(1.55)	(1.76)
RET_{t-1}	-2.911***	-3.034***	-3.781***	-4.039***	-4.086***	-3.833***	-3.68***	-2.954***
	(-10.64)	(-13.03)	(-17.17)	(-19.61)	(-18.07)	(-18.05)	(-19.10)	(-12.73)
MOM	1.84***	1.755***	1.799***	1.915***	1.758***	1.804***	1.758***	1.743***
	(40.85)	(41.84)	(44.59)	(41.74)	(42.88)	(48.08)	(48.85)	(40.88)
STD	1.217	2.13**	2.327**	2.298**				
	(1.10)	(2.06)	(2.22)	(2.14)				
Adj. R^2	0.057	0.072	0.097	0.129	0.058	0.053	0.055	0.054

2.5 Trading Strategies

In this section, we assess the profitability of trading strategies based on our OMS measures. We consider strategies based on options and the underlying. We use simple trading rules since our primary aim is not to find a return maximizing investment strategy but to assess the economic significance of the predictive relation between options market sidedness and stock returns.

Lower values of the OMS measures indicate an increase in option market one-sidedness. More specifically, lower values of OMS^+ indicate higher future returns and lower values of OMS^- signal lower future returns. Hence, we choose low levels of the OMS measure as positive or negative information trading signals. The trading signals are values of the OMS measures that are at or below 0.[34]

The general trading procedure (no matter whether it is an option or an equity based strategy) is as follows; whenever the trader obtains for the first time a trading signal in a time window that starts three weeks before maturity and ends four days before the maturity date, the investor trades on the subsequent day. Since the open interest is reported in the evening, the trader can obtain the signal only after the exchange closes. The last trade is possible on three days before maturity. In order to limit the portfolio turnover, we allow for trading only at the first time a signal arrives. All positions are sold simultaneously two days before maturity.[35]

In the first trading strategy we buy OTM call options in case of positive and OTM put options in case of negative information as indicated by the OMS based trading signal. This strategy implements the opening of new long positions that previous studies as well as our paper associate most importantly with informed trading.[36]

[34] We have tested all strategies using different trading signal thresholds partly reported in 4. The trading returns increase, the lower we require OMS to be, however, this comes at the cost of fewer observations and a higher standard deviation in the returns to the trading strategies. Therefore, we choose in what follows a relatively conservative threshold value.

[35] Note that for different ranges of trading windows we obtain qualitatively similar or even stronger results.

[36] For example, in the evening of 01/02/2006 a trader, who follows the first trading strategy, receives a positive signal, e.g., the OMS^+ takes values that are ≤ 0, for Apple Inc.. The next day he buys an OTM call option with expiration date 01/21/2006. He sells the option on the Thursday (i.e., 01/19/2006) before the option expires.

For the second strategy, we buy those stocks, for which we obtain positive information signals from OMS^+ and sell those stocks, for which we obtain a negative information trading signal. Even though we are interested in informed trading in options markets, we add this equity based strategy to alleviate concerns about option bid-ask spreads.[37, 38]

In the third strategy, we form delta-hedged portfolios in order to verify that our trading strategy results are not heavily biased by a higher moment risk compensation. Delta-hedging shuts off the directional exposure of the underlying by short-selling or buying delta shares of the underlying contract in the long call or long put strategy, respectively. Therefore, if the returns from the above trading strategies are not largely driven by higher moment risk we would expect very low returns or returns that are insignificantly different from zero.

To compute the strategy returns, we form portfolio groups with respect to an option's moneyness and time to maturity at the investment date. The moneyness groups are sorted similar as in e.g. Chakravarty et al. (2004), Lakonishok et al. (2007) or Xing et al. (2010), that is according to the ratio of the strike price K and the stock price S. For call options we use $\frac{K}{S}$ and for put options we use $\frac{S}{K}$. Clearly, a higher leverage makes an option investment more attractive for an informed investor. However, the increasing transaction costs with higher leverage (i.e. moneyness) create a trade-off between potentially higher gains and potentially higher costs. Therefore, we limit our trading strategy to option contracts with a moneyness of up to and including 1.3. The time to maturity groups are formed according to the temporal distance between the point in time when the investor receives the trading signal and the maturity date.[39]

Table 2.6 reports the trading strategy results.

[37] We use the stock closing price as reported in CRSP for the day after the trading signal.

[38] In 4 we provide results for trading strategies that account for different levels of transaction costs at different trading thresholds. The results show that our results are fairly robust to including transaction costs.

[39] We obtain the returns by first computing the average return for each trading round (i.e., maximum one month of holding period) and then averaging over all month.

Table 2.6: **Mean Portfolio Returns for OMS Based Option Trading Strategies Across Maturities and Moneyness.** The table provides mean portfolio returns for trading strategies using as trading signal OMS values at or below 0. For details how OMS is computed see Section 3.4. We form portfolio groups with respect to the options' moneyness at the investment date and the beginning time of the investment in relation to the maturity date. The moneyness groups are sorted according to the ratio of the strike price K and the stock price S. The days to maturity groups are formed according to the temporal distance in trading days between the day of the trading signal and the maturity date. We report separately the results for call (left part) and put (right part) option portfolios. Returns are in percentages and computed for the respective holding period of the investment, where two days before maturity all positions are sold. The first strategy (Panel A) corresponds either to long OTM call for positive information OMS based trading signals or to long OTM put in case of negative information OMS based trading signals. In the second strategy (Panel B) we buy those stocks, for which we obtain positive information OMS based trading signals and simultaneously short those stocks, for which we obtain negative information OMS trading signals. The third strategy (Panel C) uses delta-hedged portfolios. T-values are reported in parentheses. The sample period is January 1996 to December 2009.

Panel A: Long Option Only Strategy

		Call Option Portfolio Returns					Put Option Portfolio Returns		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	26.40	21.25	22.76		]1.0; 1.1[	16.63	14.40	15.45
		(4.42)	(31.12)	(4.55)			(4.45)	(2.29)	(2.21)
$\frac{K}{S} \in$	[1.1; 1.2[	12.2	15.67	27.02	$\frac{S}{K} \in$	[1.1; 1.2[	14.02	22.50	32.40
		(34.73)	(16.02)	(28.04)			(5.10)	(3.79)	(3.84)
	[1.2; 1.3[	9.88	8.86	17.06		[1.2; 1.3[	18.03	25.72	30.12
		(17.07)	(10.14)	(17.42)			(1.76)	(2.61)	(3.98)

Panel B: Long-Short Stock Strategy

		Time to Maturity (in trading days)		
		3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	0.14	0.64	1.50
		(6.32)	(8.17)	(9.96)
$\frac{K}{S} \in$	[1.1; 1.2[	0.16	0.73	1.59
		(7.05)	(9.61)	(10.01)
	[1.2; 1.3[	0.69	1.30	2.22
		(6.10)	(8.97)	(9.27)

Panel C: Delta-Hedged Option Strategy

		Call Option Portfolio Returns					Put Option Portfolio Returns		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	-0.21	0.17	0.43		]1.0; 1.1[	0.29	0.77	0.16
		(-0.29)	(0.60)	(1.01)			(1.55)	(1.65)	(2.17)
$\frac{K}{S} \in$	[1.1; 1.2[	0.30	0.18	0.55	$\frac{S}{K} \in$	[1.1; 1.2[	0.43	0.33	0.17
		(0.05)	(0.57)	(1.25)			(2.53)	(2.72)	(3.88)
	[1.2; 1.3[	-0.16	0.42	0.96		[1.2; 1.3[	0.17	0.13	0.22
		(-0.35)	(1.22)	(1.84)			(1.29)	(3.14)	(4.12)

On average in each trading round we are invested in option contracts for 430 different stocks due to positive OMS based trading signals and in option contracts for 415 different stocks due to negative signals depending on the strategy type. The size of the investment universe is not only interesting from a risk perspective but also from the point of view of an investor who would like to dedicate a notable amount of money into a strategy that follows option market one-sidedness.

The returns in Panel A increase with moneyness and time to maturity. The average portfolio returns for the different maturity and moneyness groups for the call option portfolio range between roughly 9% and 27% per trading round. The returns for the long put strategy are between roughly 14% and 32%. All returns are significant at a 1% level.

The results for the long-short strategy in Panel B are for all Fama-French and Carhart factor adjusted returns across maturities and moneyness groups significantly larger than zero, increase with moneyness, with the time to maturity and with the range between 0.14% and 2.22% per trading round.

Also for the delta-hedged strategy in Panel C we obtain results that are in line with our hypotheses. Once we control for Δ-risk, the significance of the returns for the call option portfolio evaporates completely and in many cases for the put portfolio. The negative correlation between volatility and returns might be an explanation for why some of the put portfolio returns remain significant.

In Appendix 4 we also report results of a second set of trading strategies, where we choose as trading signals decreases in the OMS^+ and OMS^- measures. The results are qualitatively the same as for the trading strategy that trades on the levels of the OMS measures.

One possible interpretation of the predictability and the significant trading profits for the long options and long-short stock strategy could be that options market sidedness picks-up mostly momentum signals. Therefore, in Appendix 4 we also test whether the OMS measure reflects more information than pure momentum.[40] We find that option market sidedness captures directional information in option trading that is clearly different from

[40]See Appendix 4 for details.

pure momentum signals and that also helps to identify (private) directional signals for securities that a simple momentum strategy would neglect.

2.6 Option Demand and Future Stock Market Trading

A possible alternative explanation of our results is that options market sidedness is related to illiquidity of the stock. If more options market one-sidedness (i.e., lower OMS values) indicates higher asymmetric information in the options market rather than illiquidity premia, we would expect that option demand imbalances are not able to explain the future and contemporaneous variation in stock market illiquidity. To test this, we regress the stock illiquidity measure as suggested by Amihud (2002) ($ILLQ_{Amihud}$) on our options market sidedness measures.

Second, we show in this section that two-sided (as measured by OMS) markets are associated with higher stock market trading volume. This is important since it supports that the strong return predictive power of OMS is not due to an increase in hedging demand. To this end, we regress stock market trading volume on our OMS measures.

In Table 2.7, we report the results from FMB-regressions that explore the relationship of stock market trading and options market sidedness.[41]

In columns (I) and (II), $ILLQ_{Amihud}$ is the dependent variable. In column (I) we use the lagged OMS measure as independent variable and in column (II) we use OMS contemporaneously. Neither the lagged nor the contemporaneous OMS measure yield a significant coefficient. This provides support for our hypothesis that the return predictability, which we find in the above, is not related to stock market liquidity premia.

In columns (III) and (IV), VOL_{Stock} is the dependent variable. In column (III) we use the lagged OMS measure as independent variable and in column (IV) we use OMS contemporaneously. The coefficients for all OMS measures are positive and significant, reflecting a positive relation between upward level shifts in trading activities in the stock market and a jointly increasing excess demand across all option contract types (i.e., two-sided markets). Conversely, a more one-sided options market is correlated with lower

[41] We have also estimated panel OLS regressions with and without firm level fixed effects as well as with standard errors clustered by firm level or by firm level and month. The quality of our results remains unchanged.

Table 2.7: **FMB-Regression Results for Stock Liquidity Related Measures on the OMS measure and Controls.** The table provides daily FMB-regression results. In columns (I) and (II) the dependent variable is the stock individual Amihud (2002) liquidity measure ($ILLIQ_{Amihud}$), in columns (III) and (IV) we use the stock trading volume (VOL_{Stock}) as the regressand. $ILLIQ_{Amihud}$ is computed as $(1 \times 10^{10} * |RET|)/Volume$, where $Volume$ is the daily trading volume of a stock. VOL_{Stock} is the logarithm of the daily trading volume of a stock. OMS^{+}_{t-1} and OMS^{-}_{t-1} are the lagged options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). $OMS^{2,+}_{t-1}$ and $OMS^{2,-}_{t-1}$ are the corresponding quadratic terms. The other regressors are market beta ($BETA$), size ($SIZE$), book-to-market (BM), lagged returns (RET_{t-1}), momentum (MOM), volatility (STD). The definitions of the control variables are summarized in Appendix 1. Newey-West robust t-statistics are in parentheses (20 lags). *** indicate a significance at a 1% level, ** at a 5% level and * at a 10% level. The R^2 is the average cross-sectional adjusted R^2. $No.\ Firms$ is the overall number of stocks in the regression. The sample period is January 1996 to December 2009.

Dependent Variable	$ILLIQ_{Amihud,t}$		$VOL_{Stock,t}$	
	(I)	(II)	(III)	(IV)
$Constant$	0.259***	0.259***	1.320***	1.328***
	(19.32)	(19.48)	(46.32)	(46.49)
OMS^{C}_{t-1}	0.001		0.034***	
	(0.58)		(15.52)	
OMS^{P}_{t-1}	0.000		0.039***	
	(-0.36)		(23.38)	
OMS^{C}_{t}		0.001		0.031***
		(0.69)		(15.69)
OMS^{P}_{t}		-0.001		0.035***
		(-0.81)		(22.86)
$ILLIQ_{Amihud,t-1}$	0.483***	0.482***		
	(66.57)	(66.50)		
$VOL_{Stock,t-1}$			0.781***	0.781***
			(157.8)	(158.19)
$BETA$	-0.048***	-0.048***	0.393***	0.392***
	(-8.16)	(-8.11)	(19.69)	(19.61)
$SIZE$	-0.026***	-0.026***	0.162***	0.162***
	(-20.20)	(-20.32)	(49.18)	(49.19)
RET	-0.078	-0.078	0.931***	0.93***
	(-0.91)	(-0.92)	(7.97)	(7.85)
RET_{t-1}	-0.032**	-0.034**	-0.599***	-0.6***
	(-2.07)	(-2.07)	(-21.84)	(-21.82)
MOM	0.009***	0.01***	-0.124***	-0.124***
	(2.73)	(2.94)	(-28.03)	(-27.97)
STD	-0.616***	-0.621***	7.903***	7.93***
	(-14.09)	(-14.09)	(30.86)	(30.90)
Adj. R^2	0.345	0.345	0.848	0.847
$No.\ Firms$	4,155	4,155	4,155	4,155

trading activities in the stock market. These findings supports the insight in Easley et al. (1998) that informed trading in the options market is more likely for firms with lower trading volumes. Moreover, it also emphasizes our hypothesis that trading in the stock market (and hence options market trading that is potentially related to hedging demand) is related to level shifts in the demand across all option types and moneyness categories and not to options market one-sidedness.

Overall, the results support our hypothesis that the predictive ability of OMS for stock returns is associated with asymmetric information rather than with stock market trading related risk premia, spillover effects or hedging demand.

2.7 Option Price Pressure and Informed Option Demand

A very natural extension of our study is to explore the response of options market makers to options market sidedness, or, put differently, the relation between informed option demand and price pressure in the options market.

Easley et al. (1998) find that the price pressure on call or put options increases with the relative amount of informed traders and the probability of the arrival of a positive or negative signal. Other studies like Back (1993), Cao and Wei (2010), Wei and Zheng (2010), Garleanu et al. (2009), Muravyev (2013) and Ni et al. (2008) also show that asymmetric information, and thus informed trading activities coincide with a widening of option bid-ask spreads.[42] This implies that market makers, who cannot perfectly hedge their inventories, observe in the evening, when the open interest is reported, the demand pressure in a particular option type and increase on the next day the option bid-ask spreads for the respective contract (see e.g., Easley et al. 1998, Garleanu et al. 2009, Kyle 1982, Ni et al. 2008).

Therefore, we expect that a higher options market one-sidedness (i.e., lower values of OMS) predicts wider option bid-ask spreads for the respective options that are bought by the informed investors.[43]

Using again FMB-regressions, we regress the OTM call and put spreads on the lagged OMS^{+} and OMS^{-} measure respectively and we also add stock specific control variables e.g., size, past long-term stock returns and stock return volatility and options market

[42]See e.g. Madhavan (2000) for a comprehensive review of theoretical models that establish asymmetric information and inventory risk costs of market making.

[43]Since market makers do not observe the open interest intra-daily, they can only react on the next day to the information contained in open interest changes. This implies that the profits of the informed investors are not quickly wiped out because of liquidity effects.

specific controls such as option volume.

In Table 2.8 we report the option spread FMB-regression results.[44]

Table 2.8: **FMB-Regression Results for Individual Firm Option Bid-Ask Spreads on the OMS Measure and Controls.** The table provides daily FMB-regression results using as dependent variables daily median individual firm bid-ask spreads for OTM call (model (I) and (II)) and put (model (III) and (IV)) options, respectively. OMS^{+} and OMS^{-} are the options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). For the ITM and OTM option classification see Section 2. The other regressors are size ($SIZE$), book-to-market (BM), returns (RET), momentum (MOM), volatility (STD). The definitions of the control variables are summarized in Appendix 1. $SVOL^{C}_{OTM}$ and $SVOL^{C}_{ITM}$ denote the square root of the daily median call option trading volume that are OTM or ITM. $SVOL^{P}_{OTM}$ and $SVOL^{P}_{ITM}$ denote the square root of the daily median put option trading volume that are OTM or ITM. Newey-West robust t-statistics are in parentheses (20 lags). *** indicate a significance at a 1% level, ** at a 5% level and * at a 10% level. The R^2 is the average cross-sectional adjusted R^2. $No.\ Firms$ is the overall number of stocks in the regression. The sample period is January 1996 to December 2009.

	OTM Call Spread		OTM Put Spread	
Option Spreads	(I)	(II)	(III)	(IV)
$Constant$	0.002	-0.045**	0.016	-0.09***
	(0.12)	(-2.08)	(0.81)	(-4.46)
OMS^{+}_{t-1}	-0.018***	-0.011***		
	(-4.38)	(-2.91)		
OMS^{-}_{t-1}			-0.045***	-0.039***
			(-9.24)	(-8.91)
$SIZE$		0.009***		0.009***
		(4.75)		(4.05)
RET_{t-1}		-2.261***		2.466***
		(-35.45)		(38.64)
MOM		-0.562***		0.533***
		(-27.50)		(26.63)
STD		0.896***		0.795***
		(3.12)		(2.82)
$SVOL^{C}_{OTM}$		-0.042***		
		(-28.31)		
$SVOL^{C}_{ITM}$		0.009***		
		(7.13)		
$SVOL^{P}_{ITM}$				-0.002***
				(-2.83)
$SVOL^{P}_{OTM}$				-0.038***
				(-28.55)
Adj. R^2	0.001	0.08	0.002	0.068
$No.\ Firms$	4,155	4,155	4,155	4,155

[44] In order to test whether firm effects change the quality of our results, we have also estimated panel OLS regressions with and without firm level fixed effects as well as with firm level or firm level and month clustered standard errors. Our results do not qualitatively change and we find no evidence for a substantial firm effect.

The spread regressions in columns (I) and (III) confirm the expected negative relation between the lagged OMS measures and the stock individual bid-ask spread. In addition, the results are almost identical for both call and put option spreads, which corroborates that the impact of the demand pressure is similar for the positive and negative information case. All results are robust to the controls that we include in columns (II) and (IV). Overall, the findings show that the OMS measure can be useful as a new liquidity measure in the options market.[45]

Intuitively, the reaction of the market makers to the informed demand contributes to a relative increase in future pricing inefficiencies between both market sides, for instance to violations of the put-call parity (PCP).[46] Therefore, we also test in this section whether more one-sided options markets, i.e., lower OMS measure values, predict larger violations of the PCP.

Apart from arguably the demand pressure of informed traders, there are many other reasons in the real market that determine the empirically observed violations of the PCP. For American options, the early exercise premium, and for all option types general frictions such as short-sale constraints or taxes, can lead to violations of the PCP. However, for our purposes the general fact that the PCP might be violated is irrelevant since we are interested whether higher values of the PCP violations are associated with more one-sided options markets.

Cremers and Weinbaum (2010) point out that deviations from the PCP are not only related to inefficient pricing that could be easily arbitraged away and show that informed trading may increase deviations from the PCP. In addition, in the sequential trading model of Easley et al. (1998) informed trading can result in violations of the put-call parity. Thus, we expect that options market one-sidedness also predicts absolute PCP deviations with a positive sign.

Kamara and Miller (1995) and Ackert and Tian (2001) show that PCP deviations reflect option liquidity risk by regressing PCP deviations on option liquidity risk proxies. In order

[45] In unreported results we find that options market sidedness does not affect option liquidity risk premia. This is in line with the notion of informed option trading as exploitation of private directional information, which by itself, however, remains unobserved by the uninformed investors.

[46] Previous studies such as Cremers and Weinbaum (2010) or Easley et al. (1998) provide evidence in support of this hypotheses.

to investigate the relation between our measure of option demand asymmetry and PCP deviations, we first compute:

$$|PCP\ 1| = |a^C - b^P + Ke^{-rT} - S^{bid}|, \tag{2.7.1}$$

and

$$|PCP\ 2| = |a^P - b^C + S^{ask} - Ke^{-rT}|, \tag{2.7.2}$$

where a and b denote the daily ask and bid price for the put and call options, respectively. T is the time to maturity in days, K is the strike price and r is the risk free rate. The FMB-regressions also control for several other stock individual and options market specific factors such as size, book-to-market, past returns, historical volatility or trading volume. Similarly to the spread regressions, we expect a negative coefficient for the lagged OMS measures, implying larger future absolute PCP violations when options markets are more one-sided.

The regression results in Table 2.9 yield as expected a negative predictive relation between the OMS measures and the PCP deviations. Whenever the option demand indicates asymmetric information, the future PCP deviations increase.

This supports our hypothesis that informed trading in options markets creates a one-sided demand pressure, which impacts the deviations of the pricing relations in the options market. The findings imply that informed options market demand contributes to deviations from no-arbitrage pricing relations, which puts a fundamental principle of most option pricing approaches further into question.

Table 2.9: **FMB-Regression Results for Individual Firm Put-Call Parity Violations on the OMS Measure and Controls.** The table provides daily FMB-regression results for daily median individual firm Put-Call Parity violations. Put-Call Parity violations are defined as described in Section 2.7. OMS^{+}_{t-1} and OMS^{-}_{t-1} are the options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). $OMS^{2,+}_{t-1}$ and $OMS^{2,-}_{t-1}$ are the corresponding quadratic terms. C_t is the vector of control variables that are specified below. The other regressors are market beta ($BETA$), size ($SIZE$), book-to-market (BM), lagged returns (RET_{t-1}), momentum (MOM), volatility (STD). The definitions of the control variables are summarized in 1. $SVOL^{C}_{OTM}$ denotes the square root of the daily median OTM call option trading volume. $SVOL^{P}_{OTM}$ denotes the square root of the daily median OTM put option trading volume. Newey-West robust t-statistics are in parentheses (20 lags). *** indicate a significance at a 1% level, ** at a 5% level and * at a 10% level. The R^2 is the average cross-sectional adjusted R^2. *No. Firms* is the overall number of stocks in the regression. The sample period is January 1996 to December 2009.

Put-Call Parity	PCP 1	PCP 2	PCP 1	PCP 2	PCP 1	PCP 2
Constant	0.393***	0.391***	-0.076	0.343***	-0.077	0.342***
	(40.87)	(53.00)	(-1.32)	(13.61)	(-1.35)	(13.72)
OMS^{+}_{t-1}	0.008	-0.021***	0.002	-0.023***	-0.117***	-0.014*
	(0.73)	(-6.54)	(0.15)	(-7.62)	(-3.64)	(-1.94)
OMS^{-}_{t-1}	0.012	-0.017***	-0.014*	-0.024***	-0.03**	-0.03***
	(1.14)	(-3.48)	(-1.69)	(-6.00)	(-2.17)	(-3.29)
$OMS^{2,+}_{t-1}$					0.154***	-0.013
					(4.29)	(-1.52)
$OMS^{2,-}_{t-1}$					0.02	0.009
					(1.01)	(0.94)
$BETA$			0.04***	-0.009**	0.041***	-0.009**
			(4.31)	(-2.40)	(4.32)	(-2.44)
$SIZE$			0.054***	0.012***	0.055***	0.012***
			(8.43)	(3.55)	(8.53)	(3.60)
BM			0.048***	0.006**	0.048***	0.006**
			(6.43)	(2.2)	(6.44)	(2.25)
RET_{t-1}			-0.005	0.046***	-0.011	0.047***
			(-0.22)	(4.20)	(-0.52)	(4.31)
MOM			0.062***	0.112***	0.063***	0.111***
			(4.97)	(18.46)	(4.97)	(18.33)
STD			-0.325	-1.4***	-0.293	-1.394***
			(-1.29)	(-7.96)	(-1.17)	(-7.92)
$SVOL^{C}_{OTM}$			-0.02***	-0.005***	-0.02***	-0.005***
			(-9.17)	(-6.20)	(-9.13)	(-6.18)
$SVOL^{P}_{OTM}$			0.01**	-0.006***	0.009*	-0.006***
			(1.96)	(-9.71)	(1.92)	(-9.68)
Adj. R^2	0.002	0.003	0.042	0.031	0.042	0.032
No. Firms	4,155	4,155	4,155	4,155	4,155	4,155

2.8 Conclusion

This paper combines the concept of market sidedness with excess option demand (changes in open interest) to construct a new measure of the sign and magnitude of directional information in publicly available options market data.

The guiding idea of our "options market sidedness" (OMS) measure is that if traders obtain informative signals on the future direction of stock returns, and decide to exploit their information in the options market, they create an imbalance in the excess option demand between those contract types that they are likely to buy and other contract types whose demand is predominantly driven by hedging demand, liquidity or noise trading. The larger the informed demand, the more one-sided is the options market. Informed investors tend to buy those contract types that allow them to take a leveraged position on the direction of their information (i.e., OTM options).

Hence, the measure of OMS relates the changes in open interest of OTM option contracts, that are likely to be used by directionally informed traders, with the changes in open interest for low leverage (ITM) option contracts, that are unlikely to be used by directionally informed traders and indicates trading on positive and negative signals as well as the strength of the information at an individual security level.

Using daily data of all securities at the intersection of the OptionMetrics Ivy DB, CRSP daily return files and Compustat from January 1996 until December 2009 we find: First, the OMS measure for the call (put) market predicts increasing (decreasing) stock excess returns, beyond past returns and several other controls. Second, returns for option and stock investment strategies that trade on the informed demand in options are high. Third, prior to high information events such as M&A announcements, the one-sidedness of the markets increases, consistent with the increased asymmetric information. After the announcement the option demand is again more two-sided, reflecting the decrease in information asymmetry. Fourth, other trading motives such as volatility informed trading, liquidity or hedging demand do not drive our results.

Our study also contributes empirical evidence to the potential sources of a demand related option price pressure as modeled by Garleanu et al. (2009). We show that at higher levels of informed option demand future options market liquidity is lower and pricing inefficiencies are larger.

Appendices

1 Stock Market Control Variables Definitions

Table A1: **Stock Market Control Variables Definitions.**

Variable	Definition
BM	The previous year's end-of-year book equity divided by market equity (cf., Daniel and Titman 2006).
$BETA$	Monthly market betas estimated as in Easley et al. (2002).
HI	The underlying stock's intraday high price.
LO	The underlying stock's intraday low price.
MOM	60 days backward looking cumulative return.
PRC	The underlying stock's closing price.
RV	The underlying's daily realized volatility, $\frac{HI-LO}{PRC} * 10,000$ (cf., Ni et al. 2008).
$SHROUT$	Number of shares outstanding.
$SIZE$	$log(PRC * SHROUT)$
STD	Square root of the 60 days backward looking average cumulative squared returns.

2 Controlling for Volatility Informed Trading

To validate our measure of volatility informed option demand we test, similar to Ni et al. (2008), whether the OMS^{σ} measure predicts the stock individual realized volatility RV_t by estimating the following FMB-regression:

$$RV_t = \beta_0 + \beta_1 OMS^{\sigma}_{t-1} + \beta_2 OMS^{\sigma}_{t-1} \cdot EAD_t + \mathbf{b_1 D_t} + \mathbf{b_2 C_t} + \epsilon_t, \tag{2.1}$$

with

$$\mathbf{D_t} = \left[OMS^{+}_{t-1} \quad OMS^{+}_{t-1} \cdot EAD_t \quad OMS^{-}_{t-1} \quad OMS^{-}_{t-1} \cdot EAD_t \right] \tag{2.2}$$

as the vector of variables that control for directional informed trading. $\mathbf{C_t}$ is again a set of control variables, which additionally includes current and lagged RV to control for information in current and lagged RV. The corresponding coefficient vectors are $\mathbf{b_1}$ for $\mathbf{D_t}$ and $\mathbf{b_2}$ for $\mathbf{C_t}$. EAD_t is one if t is an earnings announcement date (EAD) for the respective stock and is zero otherwise.

Previous literature shows stock return volatility is likely to increase after earnings announcements (e.g., Ni et al. 2008, Beaver 1968) and the insight that volatility informed investors are more likely to trade prior to earnings announcement dates (see Ni et al. 2008, Sarkar and Schwartz 2009), we expect a positive slope coefficient for $OMS^{\sigma} \cdot EAD_t$, i.e., $\beta_2 > 0$ and $(\beta_2 + \beta_1) > 0$. For the OMS^{σ} measure it is ambiguous, which coefficient to expect because high and low volatility bets could result in an increase in open interest of both contract types. However, we include the variable into the regression in order to control for non-EAD times. A significant positive coefficient for the OMS^{σ} measure indicates that on average a large increase in ATM straddle trading is associated with an increasing future volatility.

Since $EADs$ are public knowledge and markets tend to be largely driven by diverse beliefs prior to $EADs$ (cf., Sarkar and Schwartz 2009, Choy and Wei 2012), we expect the impact of directional informed trading before announcement dates to be negligible. Thus, for the directional OMS measure we conjecture an insignificant coefficient for the EAD interacted OMS measure. For the non-EAD interacted OMS measures, we expect, if at all, negative signs for the coefficients, implying that decreasing OMS^{+} and OMS^{-} indicate for both market sides an increase in the future realized stock return volatility. This is intuitive since the future price discovery in the stock market is most likely associated with an increase in the return volatility, no matter whether the stock returns increase or decrease.

Table A2 reports the results for the volatility predictive regressions.

We express the realized volatility in basis points, therefore the coefficients indicate daily basis point changes after e.g. the OMS measure drops from zero to minus one. To save space we omit the regression results of the controls. In row (I) the coefficients are significant at the 1% level. The coefficient for the OMS^{σ} is not straight forward interpretable due to the fact that ATM straddle bets on increasing as well as decreasing volatility would both increase the open interest in the respective call and put option pairs. However, the EAD interacted OMS^{σ} coefficient is directly interpretable since earnings announcements are usually associated with an increase in return volatility. The coefficient of the EAD interacted OMS^{σ} measure is as expected positive and $\beta_2 + \beta_1 > 0$, implying that an excess demand in call and put option ATM straddle pairs conditional on an EAD strongly indicates trading on increasing future volatilities. This corroborates our expectations and validates OMS^{σ} as indicator of volatility trading.

In row (II) we add OMS^{+} and OMS^{-} in order to verify the robustness of the results for the OMS^{σ} measure. Furthermore, this specification helps to provide support to the hypothesis that the OMS^+ and OMS^- measures are associated with directional information trading. In particular, we are interested in the coefficient of the OMS measures around $EADs$. The results show that indeed the EAD interacted directional OMS measures exhibit neither for the positive nor for the negative information case a significant coefficient. For the entire time series of the realized volatility, a lower directional OMS measure implies for both market sides increases in the future realized stock return volatility, which is in line with our expectations.

Table A2: **FMB-Regression Results for Daily Realized Return Volatilities on the Directional OMS and OMS^{σ} Measures and Controls.** The table provides daily FMB-regression results of the daily individual stock's realized volatility (RV) on the directional OMS measure and on OMS^{σ} as well as on control variables. Returns are in percentages. RV is in basis points and is defined as in Ni et al. (2008) as 10,000 times the difference of an underlying stock's intraday high and low prices divided by the closing stock price. OMS^{+}_{t-1} and OMS^{-}_{t-1} are the lagged options market sidedness measures for the positive and negative information case, respectively (for details see Section 3.4). $OMS^{2,+}_{t-1}$ and $OMS^{2,-}_{t-1}$ are the corresponding quadratic terms. OMS^{σ} is the options market sidedness measure that is related to volatility informed trading (for details see Section 3.4). EAD is a dummy that is one if the day is an earnings announcement day and zero otherwise. The results for the control variables ($Controls$) are omitted. $Controls$ includes: The other regressors are market beta ($BETA$), size ($SIZE$), book-to-market (BM), lagged returns (RET_{t-1}), momentum (MOM), volatility (STD). The definitions of the control variables are summarized in Appendix 1. $SVOL^{C}_{OTM}$ and $SVOL^{C}_{ITM}$ as the square root of the daily median call option trading volume that are OTM or ITM. $SVOL^{P}_{OTM}$ and $SVOL^{P}_{ITM}$ as the square root of the daily median put option trading volume that are OTM or ITM. Newey-West robust t-statistics are in parentheses (20 lags). *** indicate a significance at a 1% level, ** at a 5% level and * at a 10% level. The R^2 is the average cross-sectional adjusted R^2. The overall number of stocks in the regression is 4,155. The sample period is January 1996 to December 2009.

	$Constant$	OMS^{+}_{t-1}	OMS^{-}_{t-1}	$OMS^{2,+}_{t-1}$	$OMS^{2,-}_{t-1}$	OMS^{σ}_{t-1}	$OMS^{\sigma}_{t-1} \cdot EAD_t$	$OMS^{C}_{t-1} \cdot EAD_t$	$OMS^{P}_{t-1} \cdot EAD_t$	$Controls$	$Adj.\ R^2$
(I): RV_t	0.191***					-0.015***	0.241***			YES	0.099
	(11.39)					(-8.14)	(10.32)				
(II): RV_t	0.214***	-0.019***	-0.01**	0.000	-0.021***	-0.009***	0.093*	0.617	0.063	YES	0.114
	(12.04)	(-4.07)	(-2.33)	(-0.03)	(-4.46)	(-4.36)	(1.78)	(1.46)	(0.36)		

3 Information Flows between OMS and Stock Returns

To investigate the information flows between the options market sidedness measures and stock returns we test in a trivariate VAR system whether stock price changes Granger cause options market one- or two-sidedness and vice versa.

For this purpose, we model the following VAR(5) system[47]:

$$\begin{bmatrix} RET_t \\ OMS_t^+ \\ OMS_t^- \end{bmatrix} = \mathbf{c} + \sum_{p=1}^{5} \mathbf{B}_p \begin{bmatrix} RET_{t-p} \\ OMS_{t-p}^+ \\ OMS_{t-p}^- \end{bmatrix} + \boldsymbol{\epsilon}_t$$

with $\mathbf{B}_p$ as a (3×3) the coefficient matrix.

The VAR can be reformulated as an infinite vector moving average model, that is VMA(∞):

$$\mathbf{Y}_t = \boldsymbol{\mu} + \boldsymbol{\epsilon}_t + \boldsymbol{\Psi}_1 \boldsymbol{\epsilon}_{t-1} + \boldsymbol{\Psi}_2 \boldsymbol{\epsilon}_{t-2} + \ldots, \tag{3.1}$$

where $\boldsymbol{\Psi}_1$, $\boldsymbol{\Psi}_2$,... denote the MA coefficients. From (3.1) we compute impulse response functions that give the response of the system variables to a one unit shock in one variable of the VAR. We use the cumulative values of the impulse response function to measure the total impact of a shock for up to 25 days. The resulting cumulative impulse response functions for the relations of interest are displayed in Figure 3.

A one unit negative change in the innovation of the OMS^+, i.e., an increase in options market one-sidedness due to positive information, results in an increase of returns (left upper panel in Figure 3). Analogously, the right upper panel in Figure 3 illustrates that a negative shock from the OMS^- measure on stock returns results in a decrease of stock returns. The figures indicate that it takes several days until the impact of the shock in the OMS measure on returns is fully incorporated. Hence, private information in options markets at time t is only gradually incorporated into prices in $t + 1$ and throughout the following days. The results further corroborate our hypothesis that more one-sided markets indicate asymmetric information in the options markets and that indeed markets

[47] We tested a large range of different lag sizes and do not find substantial qualitative differences between the specifications. Thus, we choose one trading week as a time window.

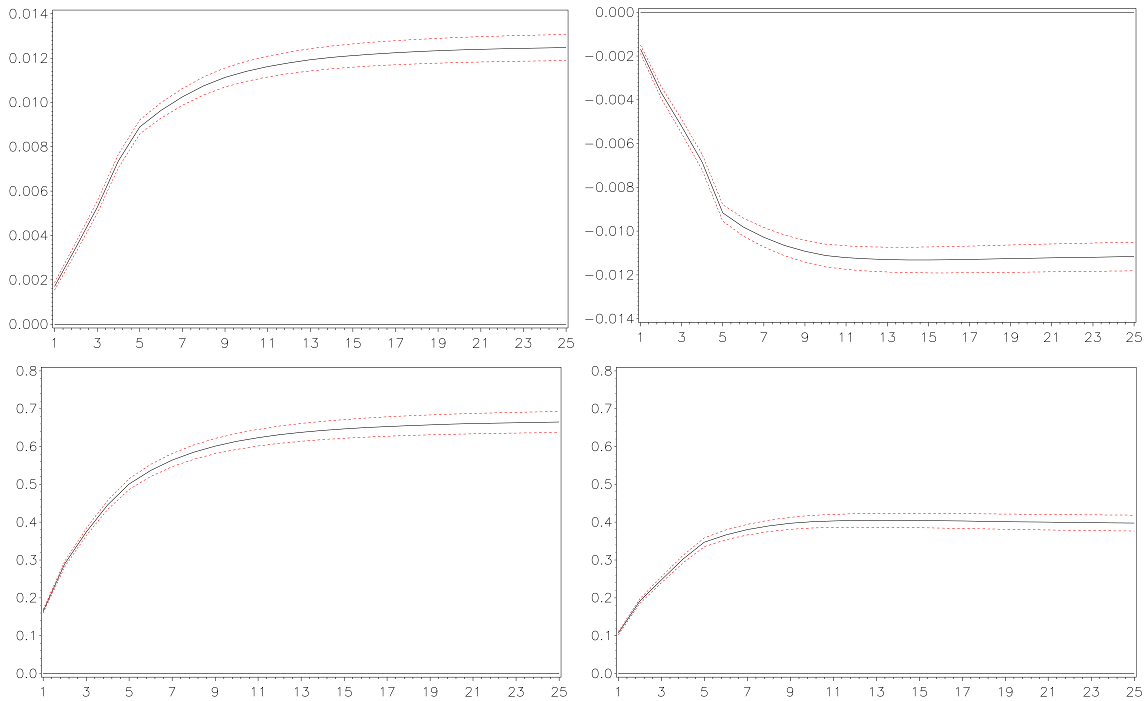
are not efficient and directional information moves with a considerable lag from options to stock markets.

Furthermore, the effects of return related shocks to the options market sidedness measures provide support to the notion that stock return news trigger joint demand shifts in the options market and make it more two-sided. Positive return innovations in the stock market result in an increase in OMS^+, reflecting an increase in options market symmetry simultaneously to the public news arrival and price readjustment in stock markets (left lower panel in Figure 3). Similarly, negative return shocks have a positive impact on OMS^-, which analogously to the positive information case reflects an increase in options market symmetry (right lower panel in Figure 3).

Figure 3: **Cumulative Impulse Response Function.** The figure shows cumulative impulse response functions using a horizon of 25 days and the VAR(5) specification:

$$\begin{bmatrix} RET_t \\ OMS_t^+ \\ OMS_t^- \end{bmatrix} = \mathbf{c} + \sum_{p=1}^{5} \mathbf{B}_p \begin{bmatrix} RET_{t-p} \\ OMS_{t-p}^+ \\ OMS_{t-p}^- \end{bmatrix} + \boldsymbol{\epsilon}_t,$$

with $\mathbf{B}_p$ as a (3×3) coefficient matrix. The upper left panel depicts the cumulative impulse response function (CIR) for a negative one unit change in the innovation of OMS^+ on stock returns. The upper right panel depicts the CIR function for a negative one unit change in the innovation of OMS^- on stock returns. The lower left panel depicts the CIR function for a positive one unit change in the innovation of the stock returns on OMS^+. The lower right panel depicts the CIR function for a negative one unit change in the innovation of the stock returns on OMS^-. The sample period for the VAR estimation is January 1996 to December 2009. The dashed lines represent 95% confidence bounds.



4 Additional Trading Strategy Results

As a first robustness check, we increase the trading threshold to study how sensitive our strategy returns are to increasing the threshold. More specifically, we choose the 25% quantile of OMS^{+} (0.11) and OMS^{-} (0.16). In each trading round we are on average invested in option contracts of 1462 different stocks associated with positive OMS trading signals and in option contracts for 1553 different stocks associated with negative signals depending on the strategy type. In Table A3 we report the trading strategy results.

In summary, the returns are lower than those for the $OMS = 0$ threshold but in general the results are robust to increasing the trading threshold to the 25% quantile. The decrease in returns is to be expected since we trade on a relatively larger fraction of weaker informative or relatively uninformative signals. On the other hand, it also shows that the results in the main text for the $OMS = 0$ threshold are not just driven by some outliers that are averaged out once we increase the window of possible trading thresholds.

Table A3: **Mean Portfolio Returns for OMS Based Option Trading Strategies Across Maturities and Moneyness.** The table provides mean portfolio returns for trading strategies using as trading signal OMS values at or below the respective 25% quantile, i.e., 0.11 for OMS^{+} and 0.16 for OMS^{-}. For details how OMS is computed see Section 3.4. We form portfolio groups with respect to the options' moneyness at the investment date and the beginning time of the investment in relation to the maturity date. The moneyness groups are sorted according to the ratio of the strike price K and the stock price S. The days to maturity groups are formed according to the temporal distance in trading days between the day of the trading signal and the maturity date. We report separately the results for call (left part) and put (right part) option portfolios. Returns are in percentages and computed for the respective holding period of the investment, where two days before maturity all positions are sold. The first strategy (Panel A) corresponds either to long OTM call for positive information OMS based trading signals or to long OTM put in case of negative information OMS based trading signals. In the second strategy (Panel B) we buy those stocks, for which we obtain positive information OMS based trading signals and simultaneously short those stocks, for which we obtain negative information OMS trading signals. The third strategy (Panel C) uses delta-hedged portfolios. T-values are reported in parentheses. The sample period is January 1996 to December 2009.

Panel A: Long Option Only Strategy

		Call Option Portfolio Returns					**Put Option Portfolio Returns**		
				Time to Maturity (in trading days)					
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	26.15	21.83	18.40		]1.0; 1.1[	15.23	12.54	11.87
		(6.30)	(4.11)	(3.92)			(3.95)	(1.86)	(2.62)
$\frac{K}{S} \in$	[1.1; 1.2[	13.12	18.09	22.16	$\frac{S}{K} \in$	[1.1; 1.2[	18.07	21.83	25.97
		(5.25)	(4.08)	(4.62)			(4.25)	(3.41)	(2.98)
	[1.2; 1.3[	15.44	8.39	30.79		[1.2; 1.3[	20.59	26.62	28.96
		(2.22)	(2.92)	(1.64)			(2.50)	(3.26)	(3.62)

Panel B: Long-Short Stock Strategy

		Time to Maturity (in trading days)		
		3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	0.50	1.24	2.01
		(6.64)	(9.67)	(10.50)
$\frac{K}{S} \in$	[1.1; 1.2[	0.62	1.43	2.21
		(6.92)	(9.88)	(10.95)
	[1.2; 1.3[	0.83	1.65	2.49
		(4.88)	(9.41)	(9.53)

Panel C: Delta-Hedged Option Strategy

		Call Option Portfolio Returns					**Put Option Portfolio Returns**		
				Time to Maturity (in trading days)					
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	0.32	0.36	0.78		]1.0; 1.1[	0.414	0.54	1.24
		(0.54)	(1.17)	(1.61)			(0.67)	(3.02)	(4.14)
$\frac{K}{S} \in$	[1.1; 1.2[	0.41	0.44	0.92	$\frac{S}{K} \in$	[1.1; 1.2[	0.28	0.71	1.36
		(0.2)	(1.37)	(1.03)			(0.23)	(3.24)	(2.97)
	[1.2; 1.3[	-0.89	0.59	1.30		[1.2; 1.3[	0.39	0.10	1.79
		(-0.34)	(1.68)	(2.59)			(1.32)	(3.41)	(2.83)

Next, we introduce transaction costs to our benchmark case, i.e., the trading threshold of OMS^+ or OMS^- being 0. Transaction costs for trading options are known to be particularly large for OTM options and are significantly larger than those for stocks. For instance, Ni (2010) and McKeon (2013) show that option trading returns for call options are likely to be negative for the average investor. However, for a more sophisticated investor with directional information and in particular also on the put market side, this might be different. Hence, it is interesting to test whether the substantial returns to the OMS based option trading strategies are relatively robust to accounting for transaction costs.

However, there are some caveats to keep in mind when interpreting these results. First, similar to Ni (2010) and McKeon (2013) we have no data on the actual trading accounts and hence on the actual trading costs; we can only generally account for transaction costs based on the option spread. Hence, these results are to be treated with caution since for instance for institutional investors (which are also most likely to be the informed traders) the transaction costs are much lower than what we assume here while for a retail investor they could also be larger. Second, our trading strategy takes the perspective of an investor, who tries to follow options market one-sidedness and is can only trade at least one day (or potentially also several days) after the informed traders exert a one-sided demand pressure on market makers. As we have seen in Section 2.7 informed trading increases future spreads. Hence, in some situations the spreads might be significantly smaller for the informed investor who as a consequence will be much less affected by transaction costs than an uninformed trader who tries to follow the information that market one-sidedness reveals. Third, one more caveat for interpreting these results is that our trading strategy does not incorporate the spread size as a side condition, which is likely to be the case at least for more sophisticated traders that often use trade algorithms that optimize transaction costs.

Table A4 reports the results for rerunning the option trading strategies for the $OMS = 0$ threshold accounting for transaction costs that amount to 25% (Panel A) and 50% (Panel B).

The results show that even after accounting for substantial transaction costs, trading on OMS still yields substantial returns. However, there is obviously a trade-off between taking on leverage and the larger spreads that are implied by OTM options. Despite the fact that OTM options are the most frequently traded option type, spreads increase substantially the further the option is OTM. Therefore for some of the trading strategy results, the profits become negative. However, for relatively longer investment periods and also for closer to the money options, the returns are relatively robust to incorporating these hypothetical transaction costs. Put options returns are also more robust to transaction costs.

We would expect that choosing a more extreme (in terms of market one-sidedness) trading threshold for OMS is also likely to improve the spread adjusted trading strategy returns. To demonstrate the effect of lowering the trading threshold value of OMS we report below trading strategy results using a threshold of OMS^+ or OMS^- being -0.2. Using this trading threshold, we invest still into a fairly large amount of option contracts for different underlyings, that is option contracts for 147 different company stocks on average per trading round for positive information trading and option contracts on 139 different stocks on average per trading round for negative information trading.

Table A5 summarizes the results for rerunning the option trading strategies applying a trading threshold of $OMS = -0.2$ and accounting for transaction costs that amount to 25% (Panel A) and 50% (Panel B).

The results highlight that the more informative the trading signal that we use, the more robust is the trading strategy to transaction costs. The put option results remain all qualitatively unchanged even when accounting for transaction costs amounting to 50%. The results for the call options are also for almost all option types and investment durations positive and significant, only for relatively far out of the money options with very short times to maturity, the profits become insignificantly different from zero on average or are negative.

Table A4: **Mean Portfolio Returns for OMS Based Option Trading Strategies Across Maturities and Moneyness with transaction costs.** The table provides mean portfolio returns for trading strategies using as trading signal OMS values at or below 0 accounting for transaction costs of 25% (Panel A) and 50% (Panel B). For details how OMS is computed see Section 3.4. We form portfolio groups with respect to the options' moneyness at the investment date and the beginning time of the investment in relation to the maturity date. The moneyness groups are sorted according to the ratio of the strike price K and the stock price S. The days to maturity groups are formed according to the temporal distance in trading days between the day of the trading signal and the maturity date. We report separately the results for call (left part) and put (right part) option portfolios. Returns are in percentages and computed for the respective holding period of the investment, where two days before maturity all positions are sold. The first strategy (Panel A) corresponds either to long OTM call for positive information OMS based trading signals or to long OTM put in case of negative information OMS based trading signals. In the second strategy (Panel B) we buy those stocks, for which we obtain positive information OMS based trading signals and simultaneously short those stocks, for which we obtain negative information OMS trading signals. The third strategy (Panel C) uses delta-hedged portfolios. T-values are reported in parentheses. The sample period is January 1996 to December 2009.

Panel A: Long Option Only Strategy Transaction Costs 25%

		Call Option Portfolio Returns					**Put Option Portfolio Returns**		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	6.40	12.75	11.96		]1.0; 1.1[	9.56	8.20	17.69
		(2.12)	(4.15)	(3.53)			(12.83)	(12.77)	(22.27)
$\frac{K}{S} \in$	[1.1; 1.2[	10.30	10.62	15.18	$\frac{S}{K} \in$	[1.1; 1.2[	5.18	9.50	28.08
		(13.65)	(15.57)	(18.73)			(4.50)	(7.43)	(18.12)
	[1.2; 1.3[	-1.20	0.18	9.50		[1.2; 1.3[	9.43	9.30	24.41
		(-5.64)	(-4.94)	(6.13)			(2.48)	(4.85)	(9.08)

Panel B: Long Option Only Strategy Transaction Costs 50%

		Call Option Portfolio Returns					**Put Option Portfolio Returns**		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	5.55	8.30	8.50		]1.0; 1.1[	6.10	1.46	12.79
		(13.75)	(2.7)	(2.51)			(1.98)	(2.27)	(16.11)
$\frac{K}{S} \in$	[1.1; 1.2[	-0.34	0.01	7.61	$\frac{S}{K} \in$	[1.1; 1.2[	-0.3	-0.3	16.92
		(-1.41)	(0.03)	(9.39)			(-0.53)	(-2.63)	(10.92)
	[1.2; 1.3[	-3.8	-2.50	-0.79		[1.2; 1.3[	-0.90	0.3	10.76
		(-8.30)	(-2.59)	(-5.15)			(-1.41)	(0.91)	(4.00)

Table A5: **Mean Portfolio Returns for OMS Based Option Trading Strategies Across Maturities and Moneyness with transaction costs.** The table provides mean portfolio returns for trading strategies using as trading signal OMS values at or below -0.2 accounting for transaction costs of 25% (Panel A) and 50% (Panel B). For details how OMS is computed see Section 3.4. We form portfolio groups with respect to the options' moneyness at the investment date and the beginning time of the investment in relation to the maturity date. The moneyness groups are sorted according to the ratio of the strike price K and the stock price S. The days to maturity groups are formed according to the temporal distance in trading days between the day of the trading signal and the maturity date. We report separately the results for call (left part) and put (right part) option portfolios. Returns are in percentages and computed for the respective holding period of the investment, where two days before maturity all positions are sold. The first strategy (Panel A) corresponds either to long OTM call for positive information OMS based trading signals or to long OTM put in case of negative information OMS based trading signals. In the second strategy (Panel B) we buy those stocks, for which we obtain positive information OMS based trading signals and simultaneously short those stocks, for which we obtain negative information OMS trading signals. The third strategy (Panel C) uses delta-hedged portfolios. T-values are reported in parentheses. The sample period is January 1996 to December 2009.

Panel A: Long Option Only Strategy Transaction Costs 25%

		Call Option Portfolio Returns					**Put Option Portfolio Returns**		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	8.15	14.84	8.70		]1.0; 1.1[	14.25	14.13	25.32
		(3.08)	(2.63)	(1.67)			(3.08)	(11.97)	(18.39)
$\frac{K}{S} \in$	[1.1; 1.2[	4.02	4.84	24.45	$\frac{S}{K} \in$	[1.1; 1.2[	31.00	14.97	29.79
		(8.30)	(7.29)	(9.65)			(6.73)	(6.96)	(14.23)
	[1.2; 1.3[	-0.20	1.20	35.95		[1.2; 1.3[	39.00	15.67	38.45
		(-10.27)	(-4.69)	(2.54)			(3.74)	(2.12)	(5.18)

Panel B: Long Option Only Strategy Transaction Costs 50%

		Call Option Portfolio Returns					**Put Option Portfolio Returns**		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	1.30	10.39	5.38		]1.0; 1.1[	14.80	7.30	20.39
		(2.40)	(1.85)	(9.60)			(2.43)	(6.22)	(14.82)
$\frac{K}{S} \in$	[1.1; 1.2[	-0.4	-1.90	6.81	$\frac{S}{K} \in$	[1.1; 1.2[	4.41	-.010	23.16
		(-3.50)	(-1.68)	(4.60)			(3.30)	(-1.08)	(9.58)
	[1.2; 1.3[	-3.40	-2.80	-0.10		[1.2; 1.3[	-0.90	18.40	13.49
		(-3.18)	(-16.25)	(-10.20)			(-1.97)	(2.12)	(2.77)

In a second set of trading strategies, we choose as trading signals decreases in the OMS^+ and OMS^- measures that are larger than the respective average decrease in OMS between date $t-2$ and $t-1$ before a high information event (see Section 2.3.2), i.e., -0.055 for OMS^+ and -0.07 for OMS^-.

In Table A6 we report mean returns of the portfolios that are formed in each trading round (roughly one month) for each trading strategy, i.e., long call, long put, long-short stock or delta-hedged, respectively. On average in each trading round we are invested in option contracts of 941 different stocks due to positive OMS based trading signals and in option contracts for 992 different stocks due to negative signals depending on the strategy type.[48]

The results for the simple long put option strategy in the right part of Panel A show that farther OTM options provide on average for each trading round higher portfolio returns. The average portfolio returns for the different maturity and moneyness groups range between 9.5% and 36% per trading round. The left part of Panel A shows the profitability of OMS based OTM long call option strategies. The profits across all maturity and moneyness groups range between 6% and 22% per trading round. The t-statistics in parentheses are significant at a 1% level in almost all cases.

Panel B reports the results for the investment strategy that goes long in those stocks, for which we obtain a positive OMS based trading signal, and that sells those stocks, for which we obtain a negative information signal from OMS^-. As in the above, we use stock returns that are orthogonalized with respect to the Fama-French and Carhart factors. All returns across maturities and moneyness groups are significantly larger than zero, increase with moneyness and with the time to maturity and range between 0.47% and 2.24% per trading round.

The economic significance of the options market sidedness hypothesis is further corroborated by the results for the delta-hedged strategy in Panel C. Most of the delta-hedged returns are statistically not different from zero and only some are slightly and significantly larger than zero. This supports the view that it is directional information rather than a

[48]For very extreme values of ΔOMS (e.g., -0.2) these numbers go down below 50 and the trading strategies yield very high positive returns but are also more volatile.

higher moment risk compensation that shows up in the returns of the above strategies.

Table A6: **Mean Portfolio Returns for ΔOMS Based Option Trading Strategies Across Maturities and Moneyness.** The table provides mean portfolio returns for option portfolio trading strategies using values of ΔOMS as trading signal that are larger than the respective average decrease in OMS between date $t-2$ and $t-1$ before a high information event, i.e., -0.055 for OMS^+ and -0.07 for OMS^-. OMS is computed as detailed in Section 3.4. We form portfolio groups with respect to the options' moneyness at the investment date and the beginning time of the investment in relation to the maturity date. The moneyness groups are sorted according to the ratio of the strike price K and the stock price S. The days to maturity groups are formed according to the temporal distance in trading days between the point in time when the investor receives the trading signal and the maturity date. We report separately the results for call (left part) and put (right part) option portfolios. Returns are in percentages and computed for the respective holding period of the investment, where two days before maturity all positions are sold. The first strategy (Panel A) corresponds either to long OTM call for positive information OMS based trading signals or to long OTM put in case of negative information OMS based trading signals. In the second strategy (Panel B) we buy those stocks, for which we obtain positive information OMS based trading signals and simultaneously short those stocks, for which we obtain negative information OMS trading signals. The third strategy (Panel C) yields returns by forming delta-hedged portfolios. For details on the trading strategies see Section 2.5. T-values are reported in parentheses. The sample period is January 1996 to December 2009.

Panel A: Long Option Only Strategy

		Call Option Portfolio Returns					Put Option Portfolio Returns		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	21.82	15.66	6.20		]1.0; 1.1[	19.40	9.56	9.52
		(5.05)	(2.93)	(1.33)			(4.16)	(2.43)	(2.41)
$\frac{K}{S} \in$	[1.1; 1.2[	13.73	17.00	11.31	$\frac{S}{K} \in$	[1.1; 1.2[	23.12	28.49	24.8
		(3.97)	(3.24)	(2.41)			(4.43)	(2.71)	(3.04)
	[1.2; 1.3[	15.96	9.10	6.62		[1.2; 1.3[	20.12	36.04	32.59
		(2.54)	(2.43)	(1.73)			(4.2)	(3.43)	(4.26)

Panel B: Long-Short Stock Strategy

		Time to Maturity (in trading days)		
		3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	0.47	0.89	1.60
		(4.39)	(6.86)	(6.68)
$\frac{K}{S} \in$	[1.1; 1.2[	0.55	1.20	1.87
		(5.07)	(8.24)	(5.62)
	[1.2; 1.3[	0.71	1.40	2.24
		(4.96)	(7.59)	(5.4)

Panel C: Delta-Hedged Option Strategy

		Call Option Portfolio Returns					Put Option Portfolio Returns		
		Time to Maturity (in trading days)							
		3-7 days	8-14 days	15-21 days			3-7 days	8-14 days	15-21 days
	]1.0; 1.1[	0.30	0.70	1.60		]1.0; 1.1[	0.14	0.54	2.28
		(1.55)	(1.44)	(1.64)			(0.77)	(0.57)	(4.44)
$\frac{K}{S} \in$	[1.1; 1.2[	0.10	0.90	1.04	$\frac{S}{K} \in$	[1.1; 1.2[	0.28	0.71	2.37
		(0.85)	(1.59)	(2.28)			(1.03)	(0.36)	(3.97)
	[1.2; 1.3[	0.19	0.12	1.70		[1.2; 1.3[	0.39	1.03	2.74
		(0.48)	(1.97)	(2.75)			(1.14)	(2.18)	(4.91)

Additional Trading Strategy Results

To test whether options market sidedness captures more that just momentum, we rerun the trading strategies using three different approaches. We first sort the stocks in each month m according to their average (m-2:m-12)-month stock return and then use the top quintile as the winner portfolio and the bottom quintile as the loser portfolio.[49] In our first testing approach, we aim at shutting off momentum signals as major explanation of the trading strategy returns. Therefore, we trade on positive signals only within the subsample of stocks in the loser portfolio, i.e., those stocks that we would sell in a momentum strategy. Additionally, we generate OMS based negative information signals and trade on them by buying puts or shorting stocks only within the winner portfolio, i.e., the portfolio of stock that we would buy in a momentum strategy. Intuitively, we restrict our positive signal trading to the sample, where we would expect the least positive momentum and the negative signal trading to the sample, where we would expect the least negative momentum. In these "reversed-momentum" subsamples we would expect substantially worse or even economically insignificant results for our trading strategies if the options market sidedness measure mainly picks-up momentum signals. The results are reported in A7. In summary, the analysis shows that the returns that we generate by selecting investments for "momentum" or "reversed-momentum" portfolios, conditioning on the OMS measures, are on average higher for those portfolios that a traditional momentum trader would not expect to perform well. This corroborates that options market sidedness captures information in option trading that is clearly different from pure momentum signals and that also helps to identify (private) directional signals for securities that a simple momentum strategy would neglect.

[49] In unreported tests we also exclude the month of January or December or both months in order to control for possible effects from window dressing and the January effect. Our results remain qualitatively unchanged, however for some moneyness-maturity groups the profits are lower.

Table A7: **Momentum and Trading on OMS.** The table provides mean portfolio returns for option portfolio trading strategies using values ≤ -0.5 of the OMS measures as trading signal. OMS is computed as detailed in Section 3.4. We compute in each panel the average returns per moneyness-maturity category for either buying OTM calls in case of positive OMS based trading signals or buying OTM puts in case of negative OMS trading signals or in a long-short stock strategy we buy those stocks for which we obtain positive information OMS based trading signals and simultaneously short those stocks for which we obtain negative information OMS trading signals. The moneyness groups are sorted according to the ratio of the strike price K and the stock price S. The days to maturity groups are formed according to the temporal distance between the point in time when the investor receives the trading signal and the maturity date. Returns are in percentages and computed for the respective holding period of the investment, where two days before maturity all positions are sold. In Panels A we restrict our sample trying to shut down momentum signals as main explanation for the trading strategy returns. Details about the trading portfolio formation are in the text above. In Panel B we restrict our sample such that we create an enhanced momentum strategy. In order to achieve this, we trade on positive signals only in the winner portfolio and on negative signals we trade only in the loser portfolio. In Panels C we use an alternative way to shut down momentum signals by restricting our sample to firms that are neither in the loser nor in the winner portfolio. For further details on the trading strategies see the above text. T-values are reported in parentheses. The sample period is January 1996 to December 2009.

Panel A: Positive Signal Trading in Loser Portfolio and Negative Signal Trading in Winner Portfolio – **"Reversed-Momentum" Strategies**

Moneyness	**Call Option Portfolio Returns**			**Put Option Portfolio Returns** **Time to Maturity** (in trading days)			**Long-Short Stock Returns**		
	3-7 days	8-14 days	15-21 days	3-7 days	8-14 days	15-21 days	3-7 days	8-14 days	15-21 days
]1.0; 1.1[	31.28	14.39	32.27	38.3	25.89	36.54	2.38	2.39	4.51
	(3.98)	(3.58)	(2.92)	(2.35)	(3.19)	(3.82)	(1.79)	(3.06)	(2.80)
[1.1; 1.2[	25.64	15.24	27.91	39.75	18.8	47.78	2.37	2.14	4.02
	(2.51)	(2.45)	(2.51)	(1.93)	(3.07)	(3.85)	(1.38)	(3.01)	(5.18)
[1.2; 1.3[	12.3	17.73	48.18	233.03	205.57	61.06	2.53	2.55	4.64
	(2.19)	(3.12)	(2.28)	(1.12)	(1.10)	(2.42)	(2.41)	(4.41)	(3.08)

Panel B: Positive Signal Trading in Winner Portfolio and Negative Signal Trading in Loser Portfolio – **"Enhanced Momentum" Strategies**

Moneyness	**Call Option Portfolio Returns**			**Put Option Portfolio Returns** **Time to Maturity** (in trading days)			**Long-Short Stock Returns**		
	3-7 days	8-14 days	15-21 days	3-7 days	8-14 days	15-21 days	3-7 days	8-14 days	15-21 days
]1.0; 1.1[	19.55	12.87	7.48	21.26	37.21	42.16	0.45	1.76	2.35
	(3.05)	(1.84)	(1.31)	(2.69)	(1.76)	(2.43)	(0.71)	(0.59)	(1.37)
[1.1; 1.2[	8.94	5.95	21.31	18.43	39.22	46.97	0.05	2.04	3.10
	(1.53)	(0.68)	(0.70)	(2.11)	(2.29)	(2.25)	(1.32)	(0.60)	(2.50)
[1.2; 1.3[	-3.25	-8.1	-10.1	14.55	20.51	9.51	-0.39	2.23	2.36
	(-1.04)	(-0.01)	(-1.48)	(1.41)	(1.56)	(1.34)	(0.50)	(0.60)	(3.45)

Panel C: Trading Strategies in The Sample of All Firms Outside the Winner or Loser Portfolio – **"Non-Momentum" Strategies**

Moneyness	**Call Option Portfolio Returns**			**Put Option Portfolio Returns** **Time to Maturity** (in trading days)			**Long-Short Stock Returns**		
	3-7 days	8-14 days	15-21 days	3-7 days	8-14 days	15-21 days	3-7 days	8-14 days	15-21 days
]1.0; 1.1[	19.92	20.16	23.52	25.95	23.93	40.14	0.83	1.10	1.98
	(4.16)	(3.61)	(3.81)	(3.13)	(2.33)	(2.53)	(2.18)	(3.27)	(4.84)
[1.1; 1.2[	4.01	7.43	24.98	28.08	36.01	52.69	0.73	1.20	1.95
	(1.58)	(2.52)	(2.62)	(2.61)	(2.56)	(3.10)	(3.88)	(3.20)	(4.15)
[1.2; 1.3[	1.35	-0.75	2.07	11.78	31.47	35.77	0.67	1.37	2.06
	(0.92)	(-0.22)	(0.93)	(1.18)	(1.83)	(2.69)	(2.23)	(4.32)	(4.66)

Chapter 3

Volatility Information in Option Demand

3.1 Introduction

Options provide investors with the unique opportunity to trade on future volatility. If the volatility expectation of certain investors changes for a fundamental reason, and those investors trade accordingly before the average investor learns about the information, the options demand is likely to be informative about future changes in volatility. At the aggregate market level higher moment risk is also tightly linked with economic conditions and hence the option trading process is also potentially informative about investors' perceptions of macroeconomic risks. Intuitively, volatility information in option demand might also be high for instance on days of substantial aggregate information asymmetry, such as FOMC decisions on adjustments of the target rate or releases of data on unemployment, GDP, consumption or other important macroeconomic aggregates. Hence, demand for index options is likely to project also investors' uncertainty about macroeconomic news. While the existence of higher moment risk premia is widely discussed and relatively well understood in the literature, we know relatively little yet about how changes in the investors' expectation of volatility materialize in their trading decisions and how the information is incorporated into the market. This work fills in this void and provides new insights about volatility information contained in index option demand. Additionally, the paper studies whether the index option trading process is also useful to measure investors' uncertainty about the macroeconomy.

To determine whether equity index option demand contains volatility information, I use the concept of option market sidedness (OMS) furthered in Kehrle and Puhan (2014) to construct a measure of volatility or skewness informed index option demand (OMS^{σ}). The measure has the following intuition; since a common trading strategy to exploit volatility information is the straddle trade (e.g., Ni et al. 2008) volatility informed trading results in a joint excess demand (changes in open interest) for at-the-money (ATM) or close-to-the-money call and put options with the same maturities.[1,2] Hence to measure volatility informed trading, I relate the changes in open interest of ATM or close-to-the-money call options to the changes in open interest of ATM or close-to-the-money put options with the same maturity.[3]

More specifically, OMS^{σ} is the correlation between open interest changes of ATM call and put options pairs that would be part of a straddle strategy in a 30-day backward looking rolling window.[4] The intuition for the measure is that higher values of the measure indicate a stronger comovement of the excess demand in call and put options that would be part of the same straddle trade, which signals an increased volatility informed demand. On the other hand, lower values of the measure indicate less trading on information about future volatility but rather about downside risk. It is well-known that market skewness is negative since the 1987 market crash because investors started to fear future negative jumps of the stock market. Consequently, if investors obtain signals that make them anticipate higher skewness risk they tend to create new positions ATM (or near-the-money) put options in order to either hedge against the market risk but also to take advantage of raising option prices if the average investor has not obtained the new information yet.

To investigate whether index option demand contains information about future market volatility and investor uncertainty about the macroeconomy, I use daily CRSP data of the S&P500 stock index (SPX) and data on all option contracts on the index as provided by OptionMetrics Ivy DB from November 2000 until December 2010.[5]

[1] A straddle that bets on an increase in volatility involves buying a put and a call with the same maturity at the same strike price, and a straddle that should exploit future decreasing volatility goes short in these option pairs. Since the option Vega is the greatest for ATM options, investors form straddle pairs by trading in ATM or close-to-the-money options in order to profit the most from volatility changes.

[2] The open interest refers to the total number of option contracts, that have not been settled in the past for the same underlying security. Since the number of outstanding option contracts is not fixed, changes in open interest are an endogenous measure of option excess demand.

[3] In what follows I refer for simplicity only to ATM options even though also close-to-the-money options that are up to 10% out-of-the money are included into the measure (see Section 2).

[4] That is, OMS^{σ} is computed as $OMS^{\sigma} = corr(\Delta OI^{C}_{ATM}, \Delta OI^{P}_{ATM})$.

[5] OptionMetrics data on SPX options starts in 1996, however, the data items needed to compute the

I find that informed excess demand in straddle option pairs has predictive power for future volatility beyond current, lagged volatility and even after controlling for changes in market risk premia, the VIX and other variables. Furthermore, focusing on macroeconomic news announcements as exogenous events of high aggregate uncertainty, I find that the changes in open interest for straddle option pairs are larger and the predictive power of OMS^{σ} for index volatilities is significantly stronger before macronews announcements and decrease after the announcement.

Trading on volatility informed option demand yields annualized Sharpe Ratios for straddle strategies that in some cases almost double the Sharpe Ratios for a long investment in the equity index. Sharpe Ratios (and returns) of the strategies increase with the strength of the volatility informed trading, in particular during periods of high volatility.

In a robustness exercise, I verify that the results are not driven by trading on directional (i.e., positive or negative) information at the index level. This finding is intuitive since index options are predominantly used as a hedging tool rather than as an instrument to take a directional bet on market-wide movements (cf. Pan and Poteshman 2006). The fact that hedging plays a major role might also be related to the substantially larger number of proprietary traders in index relative to equity options markets. Moreover, even if an investor had superior market-wide information, for instance about unemployment, it would not be clear how the market reacts to it once it becomes public news. Depending on the expectations of the investors about the impact of changes in unemployment on future economic growth, inflation, interest rates etc., stock markets might react positively or negatively to the same piece of unemployment information (cf., Boyd et al. 2005).

The paper also speaks to the relation between informed volatility demand in options and uncertainty about macroeconomic news. I find that a higher demand for straddle option pairs before macroeconomic news announcements predicts larger uncertainty about macroeconomic fundamentals. This implies that OMS^{σ} is a potentially interesting new measure of investor uncertainty about macroeconomic news. However, OMS^{σ} is not informative about the future levels or changes of the macroeconomic fundamentals by themselves (e.g., does not predict GDP or GDP growth). This further corroborates that

realized volatility of the index are only available after November 2000.

OMS^{σ} captures excess demand in index options due to volatility informed trading, rather than trading on directional signals of any kind.

I also investigate whether market makers react to volatility informed trading to protect themselves and like this gradually incorporate the information in option prices. Consistent with this, the results highlight that volatility informed demand triggers a widening of spreads, particularly before days leading up to macroeconomic announcements and in high volatility periods.

This paper contributes to the literature along several dimensions. First, so far only Ni et al. (2008) investigate volatility informed trading using data of single equity options; however, volatility information in index option demand has not yet been systematically addressed even though options demand at the index level exhibits very different features and motives of trade compared to the single equity market and despite the fact that equity index options represent a substantial fraction of the derivatives market.[6,7] Second, the paper highlights and tests an easy to compute and low frequency way of measuring volatility information in index options demand that is widely available for many markets and sufficiently long times series and that is very useful to (i) predict future volatility, (ii) differentiate between second moment or downside risk driven motives of index option trades and (iii) detect times of high market uncertainty. Third, this work also adds to a strand of literature that analyzes the impact of macro news on returns and volatilities in stock markets.[8] Yet, (volatility) informed trading in the (index) options market prior to macroeconomic announcements is still unexplored in this literature. Furthermore, I also show that volatility informed demand is useful as measure of macroeconomic uncertainty.

The rest of this paper is organized as follows. In Section 3.2, I detail the concept of

[6] For instance, according to the CBOE, the average daily volume in October 2012 was at an all-time record with 134,961 for S&P500 stock index (SPX) weekly options and 657,892 for all SPX options. Acworth (2012) reports that index options represent roughly 34% of the world wide derivative contract volume compared to roughly 26% for the global contract volume share of individual equity options.

[7] Many other studies examine various aspects of directional information trading in the single stock options market. See for instance Black (1975), Easley et al. (1998), Pan and Poteshman (2006), Kehrle and Puhan (2014) or Chakravarty et al. (2004).

[8] Examples of such studies are Boyd et al. (2005), Bernanke and Kuttner (2005), Flannery and Protopapadakis (2002), Lucca and Moench (2012), McQueen and Roley (1993a), Orphanides (1992), Pearce and Roley (1985), Nofsinger and Prucyk (2003), Beber and Brandt (2006), Vähämaa and Äijö (2010), Chen and Clements (2007), Savor and Wilson (2013) or Savor and Wilson (2012).

options market sidedness and the measure volatility informed demand. Section 2 describes the data and provides evidence about volatility informed demand around macronews announcements. Section 3.4, presents the main tests of a predictive relation between option demand and index volatility. Section 3.5 highlights the economic significance of these information in volatility informed demand with trading strategies. In Section 3.6, I investigate the impact of volatility informed demand on option market liquidity. Thereafter, Section 3.7 provides insights about the information content of volatility informed option demand about macroeconomic uncertainty. Section 3.8 concludes the paper.

3.2 Measuring Volatility Informed Option Demand

To measure volatility informed trading, I focus on ATM straddle options pairs as main trading instruments of the volatility informed. This is intuitive, since the option Vega is greatest for ATM options and volatility traders have information that prices move more (or less) without knowing the direction of the price movement. Hence, a significant increase in the association of the changes in open interest for option contracts that could be part of a straddle strategy indicates trading on volatility information (see also Ni et al. 2008, Kehrle and Puhan 2014).

So I compute the measure of volatility informed option demand OMS^{σ} on each day t, as the correlation of the changes in open interest of ATM call and put options with the same strike price and maturity in a 30-day backward looking rolling window. Formally, this reads as

$$OMS_t^{\sigma} = \frac{\frac{1}{\tau}\sum\limits_{s=t-\tau}^{t}\left(\Delta OI^{C}_{s,ATM} - \overline{\Delta OI}^{C}_{t-\tau:t,ATM}\right)\left(\Delta OI^{P}_{s,ATM} - \overline{\Delta OI}^{P}_{t-\tau:t,ATM}\right)}{\sqrt{\sigma^2_{OI^{C}_{t-\tau:t,ATM}}}\sqrt{\sigma^2_{OI^{P}_{t-\tau:t,ATM}}}}, \quad (3.2.1)$$

where τ denotes the size of the correlation window.[9]

[9] I choose this time window in order to capture as good as possible the gradual increase in informative excess demand in the options market (cf. also Kehrle and Puhan 2014). Most informed trading is likely to take place relatively close to maturity. However, ex-ante it is not clear, when exactly informed traders trade. Intuitively, informed trader are usually not going to trade on one and only one day. Therefore, using a 30-day window correlation yields at capturing the gradual increase in informative excess demand in the options market. 30 days correspond to the usual temporal distance between two maturity dates.

Intuitively, OMS^{σ} is higher whenever the changes in open interest of the options on both sides of the correlation comove stronger, indicating an excess demand in straddle pairs. On the other hand lower values of the measure indicate less volatility informed demand. The measure also captures when volatility informed investors trade on a particularly strong signal. In such cases the excess demand for ATM straddle options will be particularly strong and hence in equation (3.2.1) the demand for these options will exhibit a very high deviation from the mean level; all other things being equal this will imply a higher value of the correlation.

There are two appealing features of the correlation measure over alternative measures such as a simple ratio, a difference in mean values or simple changes in open interest. First, the correlation is a measure that standardizes the variables of interest and like this controls for differences in the volatility of the correlated variables. Second, a correlation allows me to focus on above average deviations in the changes in open interest. Hence, the correlation measure enables me to identify instances of a joint above average demand in ATM straddle option pairs.

Finally, there are several quite intuitive reasons why the correlation measure is computed from changes in open interest. Arguably the change in open interest is an endogenous measure of excess demand for options and provides a stronger link with informed option demand than for instance trading volume, which could be used as an alternative option trading measure.[10] Intuitively, the demand from informed investors is associated with the creation of new contracts (i.e., changes in open interest).[11] Hence, the number of option trades is less likely to be informative and mostly related to other trading motives such as hedging demand or liquidity, which makes trading volume a more noisy measure of option demand.[12]

Expanding or shortening the correlation window within a sensible range does not affect the quality of my results.

[10]See Kehrle and Puhan (2014) for an in-depth discussion of this issue.

[11]See for instance also the evidence in Ni et al. (2008), Pan and Poteshman (2006), Muravyev (2013), Lakonishok et al. (2007), Bollen and Whaley (2004), Easley et al. (1998), Garleanu et al. (2009) or Chesney et al. (2011).

[12]The stark difference between changes in open interest and volume is also evident in the very low unconditional correlation of changes in open interest and trading volume; the changes in open interest for S&P500 ATM (OTM; ITM) call options and trading volume is 0.3 (0.2 ;0.001) and 0.34 (0.008; 0.1) for put options.

3.3 Data and Descriptive Analysis

This section describes and summarizes the data. Furthermore, it provides evidence about volatility informed option demand around macroeconomic news announcements that validates the measure of volatility informed option demand.

3.3.1 Option and Stock Index Data

The options market data consist of all option contracts for the S&P500 stock market index at a daily frequency as provided by OptionMetrics Ivy DB.[13] The sample period is November 2000 until December 2010 resulting in 2,537 days.[14] I exclude option contracts with a maturity of more than 250 days. Overall the sample has 16,207 option contract observations.

I define the moneyness for options according to the ratio of the strike price K and the stock price S, similar to e.g., Chakravarty et al. (2004), Lakonishok et al. (2007) or Kehrle and Puhan (2014). For call options the ratio is $\frac{K}{S}$ and for put options it is $\frac{S}{K}$. An option is OTM if the respective ratio is larger than 1.10 and it is defined as ITM if the ratio is smaller than 0.90. Accordingly, ATM options have a moneyness range of 0.90–1.10.[15]

I create the daily open interest, spread and volume measures for each moneyness category, i.e., ATM/ITM/OTM call and ATM/ITM/OTM put. As an aggregated daily open interest I use the median over the open interest of option contracts in a moneyness category. The daily change in open interest for call and put options is calculated for each moneyness category.

Table 3.1 reports the summary statistics for OMS^{σ}.

OMS^{σ} has a mean value of 0.1331 and the 75% quantile is still relatively low (0.37). This is consistent with informed trading being less common than non-information based trading and also with the fact that there is a general, hedging demand related, asymmetry

[13]The daily preliminary open interest is reported at the end of each trading day and released as the final official data the following morning.

[14]The sample period is determined by the fact that the data items that I need to compute the realized volatility of the SPX are only available after November 2000.

[15]I compute additionally the moneyness ratio as $ln\left(\frac{K}{F}/IV_{ATM}\sqrt{T}\right)$, where F is the futures price and IV_{ATM} is the implied volatility of ATM options of the respective stock. This alternative definition does not change the quality of my results.

Table 3.1: **Summary Statistics.** The table provides summary statistics for the full sample period from November 2000 until December 2010. All data is daily. The table reports the mean, the standard deviation (Std), the median, the 25 percent (Q25) and the 75 percent quantile (Q75). OMS^{σ} is the option demand imbalance measure that is related to volatility informed trading (for details see Section 3.2). $SPXReturn$(%) is the excess return of the S&P 500 index over the risk-free rate. RV is in basis points and is defined as in Ni et al. (2008) as 10,000 times the difference of an underlying stock's intraday high and low prices divided by the closing stock price. VOL^{C}_{ATM}, VOL^{C}_{OTM} and VOL^{C}_{ITM} denote the square roots of the median call option trading volume that are ATM, OTM or ITM. VOL^{P}_{ATM}, VOL^{P}_{OTM} and VOL^{P}_{ITM} denote the square roots of the median put option trading volume that are ATM, OTM or ITM. N is the number of observations of each variable. The full sample period is November 2000 to December 2010.

Variable	Mean	Std	Q25	Median	Q75	N
OMS^{σ}	0.133	0.288	-0.074	0.148	0.369	16,207
$SPX\ Return$ (%)	0.010	1.381	-0.595	0.068	0.6142	2,537
RV (bp)	152.113	114.278	82.524	121.784	185.82	2,537
$VOL^{C,atm}$	8.3	5.8	4.0	7.10	11.5	16,207
$VOL^{P,atm}$	10.3	7.1	4.6	8.9	14.4	16,207
$VOL^{C,otm}$	17.8	9.1	12.2	16.3	21.2	16,207
$VOL^{P,otm}$	25.3	9.2	19.3	23.2	29.1	16,207
$VOL^{C,itm}$	4.5	3.4	2.0	3.7	5.9	16,207
$VOL^{P,itm}$	4.4	4.1	1.8	3.3	5.6	16,207

between demand for put and call index options. This demand pattern also shows up in the much larger number of trades in put options compared to call options.

As control variables I aggregate daily volume and spreads for ATM, OTM and ITM option contracts. $VOL^{j}_{t,m}$ denotes the daily median volume for $m = \{ATM, ITM, OTM\}$ call or put options, with $j = \{C, P\}$.[16] $SPREAD^{j}_{t,m}$ denotes the median daily relative bid-ask spread.

The stock market data for the S&P500 index is from the daily CRSP NYSE/AMEX/-NASDAQ return files. The index returns ($SPXReturn$) are in excess of the average one month risk free rate from the Fama risk free rates file as provided by CRSP. As a proxy for the underlying's daily realized volatility (RV), I define, similarly to Ni et al. (2008), as 10,000 times the difference of the respective underlying's intraday high and low prices divided by the closing price. Summary statistics for the index returns and realized volatility are also in Table 3.1.

Other control variables are momentum (MOM) that I compute as a 60 days backward looking cumulative return and long-term volatility (STD), i.e., the square root of the

[16] I use the median values to control for the relatively larger dispersion in the higher valued quantiles.

average cumulative squared returns in a 60 day backward looking window.

3.3.2 Volatility Information and Macro Announcements

This section uses macroeconomic news announcements to validate my measure of volatility informed option demand. Macro announcements are exogenous events, which are often followed by price adjustments in the stock market that lead temporarily to an increase in volatility (Savor and Wilson 2012). Hence, I expect that OMS^{σ} increases in the pre-announcement period (indicating an increase in volatility informed demand) and post-announcement I expect the measure to gradually decrease.

The data for macro announcement dates, analyst forecasts and the actual reported data are from Money Market Services (MMS)/Informa Global Markets provided via the Haver database.[17] Similar to for instance Green (2004), I focus on 11 important economic announcements and exclude an announcement if it is falls within a two day window after the most recent announcement. The announcements are at a monthly frequency and include unemployment, CPI, housing starts, index of leading indicators, trade balances, nonfarm payrolls, PPI, retail sales, U.S. exports, U.S. imports and FOMC meetings where information on potential changes of the Federal funds rate target is released. The overall number of announcement dates in the sample is 1159. I require at least two days between each macro announcement. After applying this rule, 568 announcement dates remain in the sample.

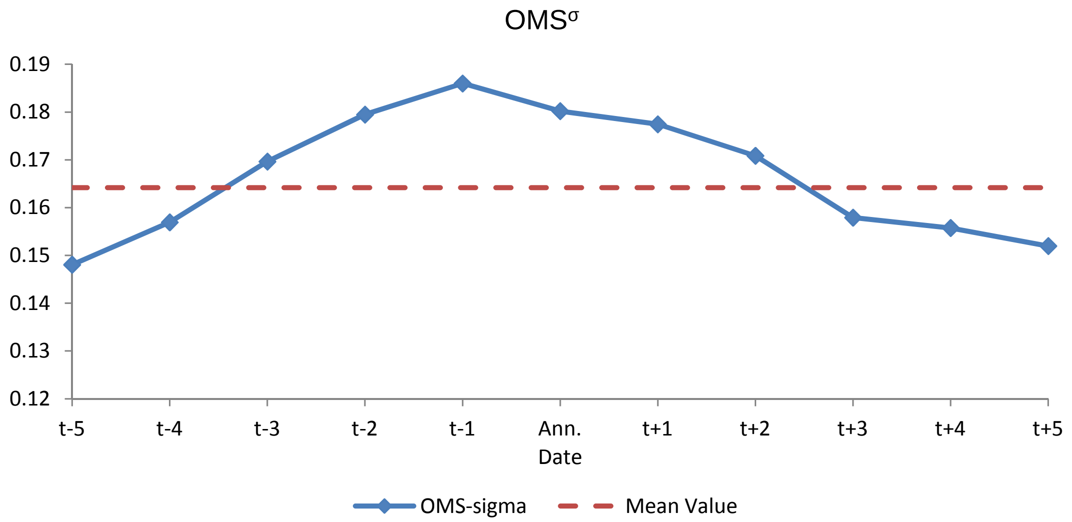
Figure 3.1 plots the average OMS^{σ} in a time window starting five days before and ending five days after the macroeconomic announcement.

The figure highlights that on the days leading to a macro announcement, the comovement of the changes in open interest for ATM straddle call and put option pairs increases as expected above the full sample average up until a mean value of 0.186 and falls again starting on the day of the announcement.

To validate that the RV increases in association with macro announcements, I compare

[17] The MMS data is the most commonly used dataset in studies that are involved with macro announcements. For instance, Sarkar and Schwartz (2009), Andersen et al. (2007), Balduzzi et al. (2001), McQueen and Roley (1993a), Green (2004), Hardouvelis (1988) and Urich and Wachtel (1984) use this dataset and Pearce and Roley (1985) extensively investigate its properties.

Figure 3.1: OMS^{σ} **and Macro Announcements.** The figure plots the average daily OMS^{σ} for a time window that starts five days before and ends five days after a macroeconomic announcement date, excluding observations with other macroeconomic announcements in the considered time window. OMS^{σ} is the option demand imbalance measure that is related to volatility informed trading (for details see Section 3.2). The overall sample period is November 2000 to December 2010.



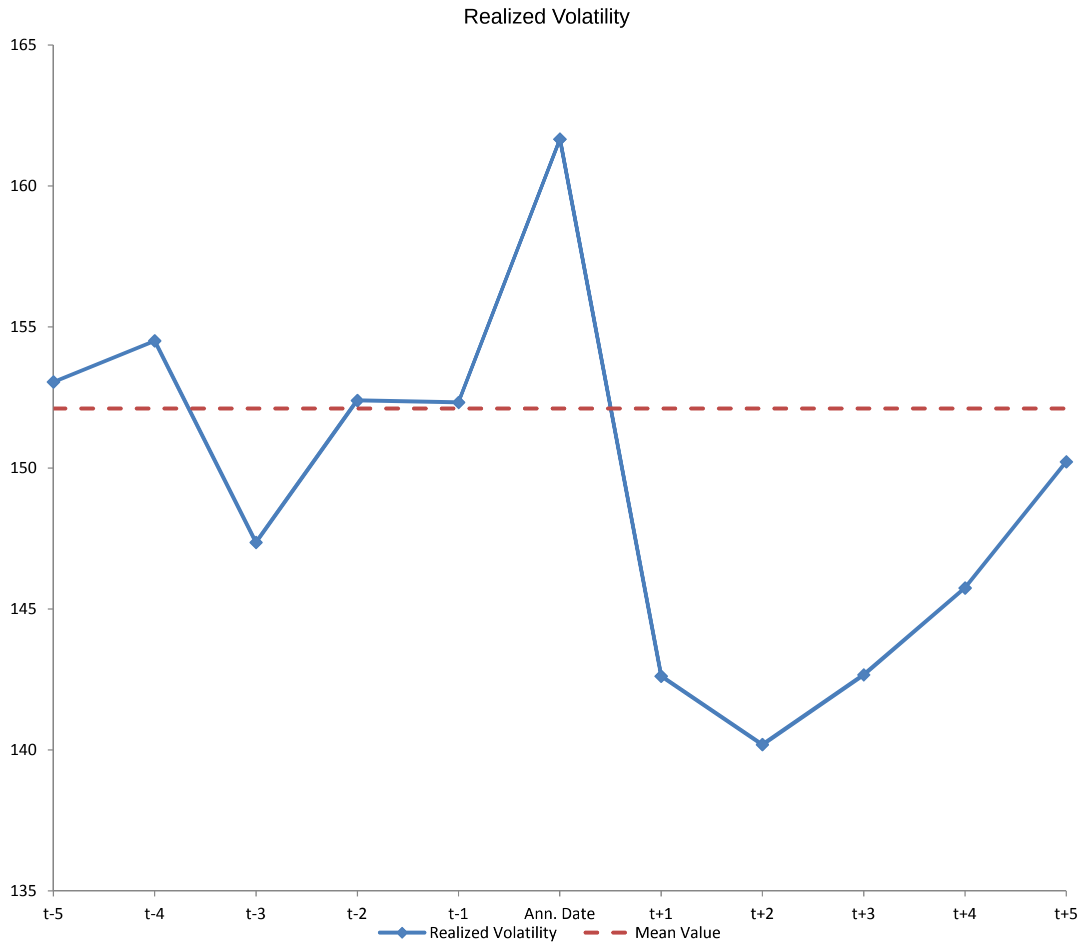
the full sample RV with the RV around macroeconomic announcement dates. Figure 3.2 plots the average RV for a window starting five days before and ending five days after a macroeconomic announcement.

The figure illustrates that on day t of the announcements (all announcements are in the morning of the announcement date) RV increases and sharply decreases

In order to further explore how realized and implied volatilities and returns of the S&P500 vary across days with different levels of the OMS^{σ} measure, Table 3.2 reports the means of these variables after sorting the data each month into OMS^{σ} quartile portfolios.

In Panel A the sorting is for the full sample. Panel B only considers days with a macro announcement on which the S&P500 index return decreased as "bad events" and Panel C considers days with a macro announcement on which the S&P500 index return increased as "good events". Using the direct reaction of the stock market as criterion to differentiate "good" from "bad" news events avoids the problem that investors seem to evaluate the same type of macroeconomic information differently at different times. Moreover, volatility and returns tend to be negatively correlated and negative news have

Figure 3.2: **Realized Volatility and Macro Announcements.** The figure plots the average daily realized volatility of the S&P500 (RV) for a time window that starts five days before and ends five days after a macroeconomic announcement date, excluding observations with other macroeconomic announcements in the considered time window. RV is computed following Ni et al. (2008) as 10,000 times the difference of the respective underlying's intraday high and low prices divided by the closing price. The overall sample period is November 2000 to December 2010.



on average a relatively larger impact on the first and second moments of the returns.

Comparing RV_t across OMS^{σ}_{t-1} groups shows in all panels that the difference in the average RV_t between high and low OMS^{σ}_{t-1} quartiles ($Hi - Lo$) is positive and sizeable. T-tests show that this difference is on average significantly different from zero in all panels. These differences are significantly larger for the macro announcement date subsamples in Panel B and C, supporting that around these dates volatility information trading is likely to increase. Tests on differences in the mean returns show across panels that the differences

Table 3.2: **Variable Means Sorted by OMS^{σ}.** The table reports the means of different variables after sorting each month the data into OMS^{σ}_{t-1} quartile portfolios (for details regarding the construction of OMS^{σ}_{t-1} see Section 3.2). In Panel A the sorting is for the full sample. Panel B only considers days with a macro announcement on which the S&P500 index return decreased and Panel C considers days with a macro announcement on which the S&P500 index return increased. $RVol$ is in basis points and is defined as in Ni et al. (2008) as 10,000 times the difference of an underlying stock's intraday high and low prices divided by the closing stock price. $SPX\ Return$ is the excess return of the S&P 500 index over the risk-free rate. $IVol$ is in basis points and is the implied volatility of the S&P500, computed as in Ni et al. (2008). *** indicate a 1% level of significance, ** a 5% level of significance and * a 10% level of significance for a t-test on an average significant difference from zero for the $Hi - Lo$ values of the the respective variable means across OMS^{σ} groups. The full sample period is November 2000 to December 2010. The number of observations is 16,207 and 2,537 days.

		$RVol(bp)$	$SPX\ Return(\%)$	$IVol(bp)$
Panel A: Full Sample				
OMS^{σ}_{t-1}	Low	124.419	0.016	1867.539
	2	128.781	0.011	1902.443
	3	164.497	0.031	2159.976
	High	201.542	0.0108	2526.483
	$Hi - Lo$	77.123***	-0.005	658.944***
Panel B: Bad News Events		$RVol(bp)$	$SPX\ Return(\%)$	$IVol(bp)$
OMS^{σ}_{t-1}	Low	126.186	-0.543	1872.378
	2	127.493	-0.639	1894.849
	3	141.667	-0.583	2073.199
	High	231.360	-0.932	2556.892
	$Hi - Lo$	105.174***	-0.390***	684.514***
Panel C: Good News Events		$RVol(bp)$	$SPX\ Return(\%)$	$IVol(bp)$
OMS^{σ}_{t-1}	Low	132.382	0.681	1806.406
	2	139.100	0.696	1920.197
	3	184.56	0.940	2183.079
	High	224.116	1.040	2600.453
	$Hi - Lo$	91.7345***	0.358***	794.047***

for each group are significant between the event date sample and the full sample.[18] The differences are insignificant between the bad and the good news groups. Overall these results provide further evidence for the non-directional nature of the information in the excess option demand that is picked up with OMS^{σ}_{t-1}.

Turning to the OMS^{σ}_{t-1} sorted average index return groups, one interesting observation

[18]The test results are omitted in the table to keep it better readable but naturally they are available on request.

is that for the full sample across OMS^{σ}_{t-1} there is no significant difference in the mean returns, which is another indicator for the non-directional information content of OMS^{σ}_{t-1}. Between Panel B and C, there are obviously large return level differences. Since I have defined the good and bad events relative to stock index increases or decreases after the announcement, it is natural that the returns of the stock index are overall lower and in fact highly negative in Panel B, whereas in Panel C the returns are positive and relatively high. Across OMS^{σ} within the bad news and the good news subsample there are differences in returns, which correlate with the higher RV_t across OMS^{σ}_{t-1} groups.

The descriptives for the implied volatility ($IVol_t$) show, compared to the RV_t, similar yet less strong patterns. The differences across OMS^{σ}_{t-1} for each subsample are similar and substantially lower (in relative terms) than for the RV_t. Similar to the results for the RV_t, tests on differences in the means show that the differences for each group are significant between the event date and the full sample. However, the differences between the bad and the good news groups are again insignificant.

3.4 Informed Option Demand and Future Volatility

To test the predictive power of OMS^{σ} for future volatility, I follow Ni et al. (2008) and estimate linear regressions of the realized S&P 500 index volatility (RV) on the lagged OMS^{σ} measure and different controls with Newey-West robust standard errors.

$$RV_t = \beta_0 + \beta_1 OMS^{\sigma}_{t-j} + \beta_2 OMS^{\sigma}_{t-j} \cdot I_t + \mathbf{b_1}\mathbf{D} + \mathbf{b_2}\mathbf{C} + \epsilon_t, \tag{3.4.1}$$

with $j = 1, \ldots, 5$ and

$$\mathbf{D} = \Big[RV_{t-1} \ldots RV_{t-5} \quad OMS^{+}_{t-j} \quad OMS^{+}_{t-j} \cdot I_t \quad OMS^{-}_{t-j} \quad OMS^{-}_{t-j} \cdot I_t \quad I_t \Big] \tag{3.4.2}$$

is the vector of variables that control for directional informed trading. I add lags of the RV to control for information in RV that is accessible at the same time as and prior to OMS^{σ}_{t-1}. I_t is one if t is a macroeconomic news announcement date and is zero otherwise. I also control for the VIX, as a measure of the market's ex-ante perception about volatility risk. OMS^{+} and OMS^{-} are controls for positive and negative informed option demand.[19] $\mathbf{C}$ is a set of control variables, which additionally includes option volume $VOL^{j}_{t,m}$, where $VOL^{j}_{t,m}$ denotes the daily volume for $m = \{ATM, ITM, OTM\}$ call or put options, with $j = \{C, P\}$, and a measure for the standard deviation of the cumulated return of the past 60-days (STD). The corresponding coefficient vectors are $\mathbf{b_1}$ for $\mathbf{D}$ and $\mathbf{b_2}$ for $\mathbf{C}$.

Table 3.3 reports the results for the RV regressions. Panel A, summarizes the results for different regression models for which j is always equal to 1.

[19]Similar to Kehrle and Puhan (2014) I compute these measures to capture a potential impact of directional trading. So I correlate the change in open interest of options that provide investors with high leverage (and hence are attractive for informed investors) with the changes in open interest of low leverage options; i.e., $OMS^{+} = corr(\Delta OI^{C}_{OTM}, \Delta OI^{P}_{ITM})$ and $OMS^{-} = corr(\Delta OI^{P}_{OTM}, \Delta OI^{C}_{ITM})$. Lower values of the measure indicate more directionally informed demand, in the terminology of Kehrle and Puhan (2014) the option market is more one-sided. A higher value of the measures indicates more heterogenous beliefs.

Table 3.3: **Regression Results for Daily Realized Stock Index Volatilities on OMS^{σ} and Controls.** The table provides daily regression results of the daily realized volatility (RV) of the S&P500 on OMS^{σ} as well as on control variables. The results for some control variables are omitted to save space, however, they are listed and defined below. In Panel A, RV is regressed in models (I)–(VI) on different explanatory variables. In Panel B, RV is regressed on all previous control variables and the OMS^{σ} variables with an increasing number of lags. RV is in basis points and is defined as in Ni et al. (2008) as 10,000 times the difference of an underlying stock's intraday high and low prices divided by the closing stock price. The regressions include 5 RV *lags* as controls. OMS^{σ} is the option demand imbalance measure that is related to volatility informed trading (for details see Section 3.2). I in an indicator variable that is equal to one if trade day t is an economic announcement day. The indicator is also added non interacted as unreported control. OMS^{+} and OMS^{-} are the options market sidedness measures for the positive and negative information case, respectively, that are obtained by correlating call and put option contracts (for details see Section 3.2). VIX is the CBOE Market Volatility Index. The control variables are: MOM, VOL^{C}_{OTM}, VOL^{C}_{ATM}, VOL^{C}_{ITM}, VOL^{P}_{OTM}, VOL^{P}_{ATM} and VOL^{P}_{ITM}. STD is obtained from the daily return data as the standard deviation of the cumulative returns of the stock index over a 60 days backward looking window. VOL^{C}_{OTM}, VOL^{C}_{ATM} and VOL^{C}_{ITM} are the square roots of the daily median call option trading volume that are OTM, ATM or ITM. VOL^{P}_{OTM}, VOL^{P}_{ATM} and VOL^{P}_{ITM} are the square roots of the daily median put option trading volume that are OTM, ATM or ITM. Newey-West robust t-statistics are in parentheses (20 lags). The R^2 is the adjusted R^2. N is the number of observations. The full sample period is November 2000 to December 2010. The number of observations is 16,207 and 2,537 days.

Panel A: Different Regressions Models
Realized Volatility S&P 500

Model	*Const.*	OMS^{σ}_{t-1}	$OMS^{\sigma}_{t-1} \cdot I_t$	OMS^{σ}_{t}	OMS^{+}_{t-1}	OMS^{-}_{t-1}	$OMS^{+}_{t-1} \cdot I_t$	$OMS^{-}_{t-1} \cdot I_t$	VIX_{t-1}	*RV lags*	*Controls*	*Adj. R^2*	N
(I)	0.308	0.131	–	–	–	–	–	–	–	Yes	Yes	0.602	2,537
	(5.52)	(2.33)	–	–	–	–	–	–	–				
(II)	0.303	0.060	0.226	–	–	–	–	–	–	Yes	Yes	0.603	2,537
	(5.40)	(0.85)	(1.97)	–	–	–	–	–	–				
(III)	0.302	0.542	0.219	-0.495	–	–	–	–	–	Yes	Yes	0.641	2,537
	(5.37)	(1.42)	(1.91)	(-2.26)	–	–	–	–	–				
(IV)	0.259	0.3654	0.2683	-0.307	0.040	0.031	–	–	–	Yes	Yes	0.641	2,537
	(3.03)	(1.49)	(2.11)	(-1.27)	(0.62)	(0.45)	–	–	–				
(V)	0.263	0.359	0.266	-0.301	0.055	0.001	-0.040	0.092	–	Yes	Yes	0.647	2,537
	(3.07)	(1.45)	(1.89)	(-1.24)	(0.73)	(0.01)	(-0.39)	(1.00)	–				
(VI)	-0.106	0.313	0.258	-0.413	0.004	0.110	-0.072	0.111	0.035	Yes	Yes	0.652	2,537
	(-1.06)	(1.28)	(1.87)	(-1.75)	(0.05)	(1.47)	(-0.70)	(1.23)	(4.39)				

Panel B: Regressions with Higher OMS Lags j
Realized Volatility S&P 500

j	*Const.*	OMS^{σ}_{t-j}	$OMS^{\sigma}_{t-j} \cdot I_t$	*RV lags*	*Controls*	*Adj. R^2*	N
2:	0.294	0.143	-0.034	Yes	Yes	0.601	2,537
	(5.29)	(1.93)	(-0.28)				
3:	0.299	0.156	0.235	Yes	Yes	0.602	2,537
	(5.32)	(1.83)	(1.91)				
4:	0.294	0.148	-0.148	Yes	Yes	0.603	2,537
	(5.25)	(2.70)	(-1.43)				
5:	0.298	0.139	0.188	Yes	Yes	0.601	2,537
	(5.34)	(2.26)	(1.67)				

The results for the first regression model show that as expected OMS^{σ} has predictive power for RV beyond current and lagged volatility. The positive highly significant coefficient indicates that on average, the volatility informed option demand increases prior to future increases in the index RV.

In the next row (II), I add OMS^{σ}_{t-1} signed with a dummy (I) that is equal to 1 if on day t there is a macroeconomic announcement. After macroeconomic announcements on average the volatility of the S&P500 increases for a certain period of time and therefore volatility informed traders are more likely to trade in the options market on volatility signals prior to macroeconomic news announcement dates. Consistent with this the coefficient for the interacted OMS^{σ}_{t-1} is positive and highly significant.[20]

In row (III) I also include the contemporaneous OMS^{σ} term. This does not change the quality of the results. The coefficient of OMS^{σ}_{t} exhibits the opposite sign compared to the coefficient of the lagged variable. This is intuitive since at the time when the news is revealed, the measure should start to take lower levels, indicating less asymmetric information regarding volatility.

In the next regression model (column IV), I include the lags of OMS^{+} and OMS^{-} to control for trend or risk premia related trading motives. The coefficients for both measures are insignificant, which is in line with the finding of Pan and Poteshman (2006) that index option trading contains no directional information. This finding is also intuitive because it is not clear in which direction the overall market reacts to these news. Hence, an investor with directional information about macroeconomic fundamentals, such as GDP or labor market news, would arguably very unlikely trade on this information with a directional option investment. The results for OMS^{σ}_{t-1} are not affected by including OMS^{+} and OMS^{-}.

In regression model (V), I also add OMS^{+} and OMS^{-} interacted with the macro announcement dummy to validate that even before these events of high macroeconomic information asymmetry, directional option demand has no impact on my results. As expected the coefficients of the interaction terms are insignificant and the results for OMS^{σ}_{t-1}

[20]The unreported coefficient of the macro announcement dummy, which controls for volatility changes on macro announcement dates that are unrelated to volatility informed trading, is also positive and significant.

remain unaffected.

In the last regression model (VI) I add the first lag of the VIX as an additional control. The VIX contains information about investors' ex-ante perception of future volatility risk and is widely used as an indicator for future volatility. Hence, it is interesting to study whether the information in the options excess demand as measured by OMS^{σ} is any different from what we could learn anyway from using the VIX. The results show that indeed OMS^{σ} adds volatility information since the quality of the results for the OMS^{σ} related variables is not changed due to the addition of the VIX to the regression.

In Panel B, I predict, similar to Ni et al. (2008), realized volatility separately using OMS^{σ} with an increasing values of lagsize j. At least some of the j lags of OMS^{σ} should also exhibit positive significant coefficients if OMS^{σ} captures actual informed demand. Indeed, the coefficient for OMS^{σ} is positive and highly significant for all $j \geq 2$. For the third and the fifth lag of OMS^{σ}, the $OMS^{\sigma} \cdot I$ is also positive and significant. The results emphasize that OMS^{σ} persistently picks up volatility information.

In Appendix 1 I show in a robustness exercise that OMS^{σ} has no predictive power for future index returns, which supports that OMS^{σ} captures neither directional information, nor expected market risk premia nor any such trading motives. Furthermore, 1 shows that OMS^{+} or OMS^{-} have no predictive power for future index returns, highlighting that index option demand is not driven by directionally informed demand.

3.5 Trading Strategies

The results from the regression analysis provide strong evidence for OMS^{σ} as a measure of volatility informed index option demand. Yet, the question remains whether the information in OMS^{σ} is actually significant also in economic terms. Therefore, I consider next the profitability of trading strategies conditional on the OMS^{σ} measure.

If an increase or high values of the OMS^{σ} indeed capture a volatility informed excess demand in straddle option pairs, a trading strategy that conditions on an increase OMS^{σ} should result in at least non-negative or increasing returns.

Hence, I use the relative percentage changes in the measure, i.e., $(\Delta OMS^{\sigma}/OMS^{\sigma}){*}100$, as trading signal. Choosing a trading signal of this kind has the advantage that even in the low volatility years, where the OMS^{σ} measure can be negative, and yet experiences several sharp run-ups, it is a useful measure to capture the effects of the joint excess demand changes in options straddle pairs that obviously contain volatility information.

Using this trading signal, I set up a straddle trading strategy that should mimic the trading behavior of the volatility informed investors. I compute the returns for a range of OMS^{σ} trading signal values. The trading strategy assumes that as soon as a trader obtains a signal in a time window that starts three weeks before maturity and ends on the Monday before the maturity date (the maturity date is usually a Saturday), the investor takes a straddle position on the subsequent day. Since the open interest is reported in the evening, the trader can obtain the signal only after the exchange closes. The last trade is possible on the Tuesday before maturity. All positions are sold simultaneously on the Tuesday four days before maturity.[21]

Table 3.4 provides annualized Sharpe Ratios for different benchmarks. The first ($SR_{ATM-SPX}$) uses the SPX index as benchmark. The second is the most widely used version benchmarked with the risk-free rate (SR_{ATM-rf}). Furthermore, I compute the difference between SR_{ATM-rf} and the Sharpe Ratio of a long investment in the index that is bought and sold at the same time as the straddle and benchmarked with the risk-free rate (SR_{SPX-rf}). The most-right column reports t-statistics for the long straddle strategy for the average strategy returns in each trading round (i.e., roughly one month). Panel A summarizes the results for the full sample, Panel B for the years with an average RV that is larger than the sample average and in Panel C for years with an average RV that is below the sample average. Separating the sample in this way might provide interesting insights on the nature and strength of the volatility information in option excess demand at different times.

In Panel A the results show that for small and moderate increases the strategy generates significant profits that also beat a simple investment in the market. However, for

[21] Note that for different ranges of trading windows I obtain qualitatively similar or even stronger results. However, in particular to avoid close to maturity effects on option prices, I prefer a more conservative version of the trading strategy that requires the clearing of all investments several days before maturity (cf. Day and Lewis 1988).

Table 3.4: **Trading on OMS^{σ}.** The table provides performance statistics for straddle pair option trading strategies using different threshold values of the OMS^{σ} measure as trading signal as detailed in Section. OMS^{σ} is computed as detailed in Section 3.2. Panel A reports results for the full sample, Panel B provides results for high volatility years in the sample and Panel C for low volatility years in the sample. $SR_{ATM-SPX}$ is the annualized Sharpe Ratio for the straddle strategy return for each trading round using the SPX as benchmark. SR_{ATM-rf} is the annualized Sharpe Ratio for the straddle strategy return for each trading round using the risk-free rate as benchmark. SR_{ATM-rf}- SR_{SPX-rf} is the difference between the annualized Sharpe Ratio for the straddle strategy return for each trading round using the risk-free rate as benchmark and the annualized Sharpe Ratio benchmarked with the risk-free rate for a strategy that goes long in the market if OMS^{σ} reaches the threshold and sells the position at the same date where the option straddle position would be sold. For further details on the trading strategies see Section 3.5. T-values are reported in parentheses. The full sample period is November 2000 to December 2010. The number of observations is 16,207 and 2,537 days.

Panel A: Full Sample				
$\Delta OMS^{\sigma}(\%)$	$SR_{ATM-SPX}$	SR_{ATM-rf}	$SR_{ATM-rf} - SR_{SPX-rf}$	t-value
$(0, 10]$	4.501	4.523	0.233	(6.18)
$(10, 50]$	5.703	5.673	1.181	(2.33)
$(50, 80]$	0.663	0.554	-8.74	(2.12)
$(80, 100]$	-0.902	-0.805	-6.668	(1.35)
$(100, +\infty)$	1.91	1.893	1.529	(1.36)
Panel B: High Volatility Sample				
$\Delta OMS^{\sigma}(\%)$	$SR_{ATM-SPX}$	SR_{ATM-rf}	$SR_{ATM-rf} - SR_{SPX-rf}$	t-value
$(0, 10]$	3.437	3.471	-0.13	(3.49)
$(10, 50]$	7.137	7.098	-2.702	(2.30)
$(50, 80]$	4.012	3.882	4.051	(1.90)
$(80, 100]$	13.65	13.543	7.86	(1.86)
$(100, +\infty)$	10.063	9.88	0.08	(2.27)
Panel C: Low Volatility Sample				
$\Delta OMS^{\sigma}(\%)$	$SR_{ATM-SPX}$	SR_{ATM-rf}	$SR_{ATM-rf} - SR_{SPX-rf}$	t-value
$(0, 10]$	4.687	4.737	0.4251	(5.08)
$(10, 50]$	2.911	2.978	0.831	(1.71)
$(50, 80]$	-1.968	-2.011	-22.554	(0.82)
$(80, 100]$	-8.736	-8.476	-12.77	(0.63)
$(100, +\infty)$	-2.067	-1.9825	-3.023	(1.19)

$\Delta OMS^{\sigma}/OMS^{\sigma}$ trading signals on the interval above 80% and until an increase of 100% the Sharpe Ratios become negative and the returns are not significantly different from zero anymore. For the interval with changes of OMS^{σ} that are larger than 100%, the Sharpe Ratios are positive again and the strategy also beats, in terms of Sharpe Ratio, the long index alternative, however the returns are on average not significantly different from zero. For the interpretation of the results, I prefer to be very cautious in interpreting directly the magnitudes of the Sharpe Ratios. Broadie et al. (2009) highlight, that the returns to straddle strategies are very risky and most often violate the normality assumption behind the Sharpe Ratios. This seems to be also reflected in the results for the trading strategies with more extreme trading signals.[22]

The mixed results in Panel A might be related to the fact that in low volatility times there is less volatility information trading in the market and therefore the signals that OMS^{σ} captures are significantly weaker. If this is the case, I should find some evidence for this in Panels B and C, where I implement the trading strategy separately for high and low volatility times.

The results in Panel B emphasize that in high volatility times, there is a lot more volatility information in the excess option demand of straddle option pairs. All profits are highly significantly different from zero and the Sharpe Ratios are fairly high, up to 13.65 and up to twice as large as the Sharpe Ratio of the long index strategy; only in two cases of smaller increases of OMS^{σ} the value of SR_{SPX-rf} is higher than SR_{ATM-rf}.

Considering next the results for the low volatility years in Panel C reveals that indeed only in case of small or moderate increases in the volatility trading measure, the strategy generates returns that are significantly different from zero and also have a Sharpe Ratio that is slightly better than the Sharpe Ratio of the long index strategy.

3.6 Volatility Informed Demand and Option Liquidity

Market makers can observe at the end of the day the open interest and like this form an opinion about the potential trading motives of the investors.[23] Previous work shows for single equity options that market makers, that cannot perfectly hedge, try to protect themselves against directional and volatility informed demand by setting wider spreads (on the next trading day).[24] Hence, in this section I investigate whether this is also the case for volatility informed trading in index options.

One concern might be that market makers may also respond with a widening of spreads

[22]For this reason I also choose not to rely on comparing mean returns but only performance statistics that take the risk, which is related to the returns, into account.

[23]Market makers observe the open interest at the end of each day; hence, the information contained in open interest changes only enters the market not before the subsequent day. This implies that the profits of the informed investors are not quickly wiped out because of liquidity effects.

[24]See e.g., Easley et al. (1998), Garleanu et al. (2009), Kyle (1982), Kehrle and Puhan (2014) or Ni et al. (2008).

to higher uninformed trading activity, hence it is important to disentangle both explanations from each other (cf., Ni et al. 2008). In order to clearly identify instances, which are preceded by high aggregate information asymmetry, I use in this section macroeconomic news announcements again as exogenous events of high aggregate information asymmetry and increased levels of volatility.

To test whether volatility informed index option demand affects liquidity levels in the index options market, I regress the spreads of the ATM call and put options separately on OMS^{σ}_{t-1}, OMS^{σ}_{t-1} interacted with a dummy I_t that is 1 in case of a macro announcement day, the dummy itself and further controls for implied volatility, past returns and option volume.

The regression model reads as

$$SPREAD^{j}_{t,ATM} = \beta_0 + \beta_1 OMS^{\sigma}_{t-1} + \beta_2 OMS^{\sigma}_{t-1} \cdot I_t + \beta_3 I_t + \beta_4 OMS^{\sigma}_{t-1} \cdot I_{VolSt} + \beta_5 I_{VolSt} + \mathbf{bC} + \epsilon_t, \tag{3.6.1}$$

with $j = \{C, P\}$ denoting whether it is the call or put option spread, $\mathbf{C}$ subsumes the control variables, such as the first lag of the implied volatility IV_{t-1}, option volume $VOL^{j}_{t,ATM}$ or a measure for the cumulated past 60-day returns MOM. Since the impact of volatility informed trading is likely to depend on the volatility regime (high/low), I also estimate regression models that include interaction terms of OMS^{σ}_{t-1} with dummies (I_{VolSt}) that are equal to one in a high (low) volatility state and zero otherwise. A high volatility state is defined as a year where the average RV is above the average full sample RV. The standard errors are heteroscedasticity adjusted (Newey-West) and the R^2 is adjusted for the number of regressors.

The results for the spread regressions are in Table 3.5. The results for the call spreads are in columns (I)–(IV) and in the columns (V)–(VIII) provide the results for put options.

The results in Table 3.5 show that in all columns the coefficient for the announcement date interacted OMS^{σ}_{t-1} measure is positive and highly significant. This supports that as informational asymmetry increases in the days leading up to the macroeconomic announcements, the impact of volatility informed demand also increases. This is also consistent with market makers trying to protect themselves after observing a greater dissemination

Table 3.5: **Volatility Trading and Liquidity Levels.** OMS^{σ} is the option demand imbalance measure that is related to volatility informed trading (for details see Section 3.2). I is an indicator that is 1 if the day is an announcement day and the indicator is 0 otherwise. IV is the equally weighted average of the implied volatilities of the straddle option pairs that are used to compute OMS^{σ}. VOL^{C}_{ATM} and VOL^{P}_{ATM} are the square roots of the daily median ATM call and put option trading volume. MOM is obtained from the daily return data as cumulative returns of the stock index over a 60 days backward looking window. $\mathbf{1}_{HighVola}$ is a dummy that is 1 if a year has an above average RV and is zero otherwise. $\mathbf{1}_{LowVola}$ is a dummy that is 1 if a year has an above average RV and is zero otherwise. Newey-West robust t-statistics are in parentheses (20 lags). The R^2 is the adjusted R^2. The full sample period is November 2000 to December 2010. The number of observations is 16,207 and 2,537 days.

	ATM Call Spread				**ATM Put Spread**			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Const.	-0.129	-0.262	-0.246	-0.220	-0.035	-0.239	-0.223	-0.231
	(-2.22)	(-3.72)	(-3.26)	(-2.48)	(-0.59)	(-3.33)	(-2.87)	(-2.52)
$OMS^{\sigma}_{t-1} \cdot I_{t+1}$	0.278	0.224	0.261	0.260	0.450	0.393	0.405	0.402
	(2.79)	(2.29)	(2.14)	(2.13)	(4.57)	(4.07)	(3.31)	(3.29)
OMS^{σ}_{t-1}	-0.246	-0.203	-0.350	-0.080	-0.259	-0.256	-0.436	-0.031
	(-3.10)	(-2.59)	(-2.82)	(-0.59)	(-3.21)	(-3.20)	(-3.53)	(-0.22)
IV_{t-1}	0.443	0.464	0.178	0.210	-0.044	0.464	0.224	0.268
	(1.55)	(1.41)	(0.46)	(0.54)	(-0.15)	(1.38)	(0.56)	(0.67)
I_{t+1}	0.212	0.180	0.167	0.167	0.207	0.177	0.180	0.180
	(6.19)	(5.26)	(4.14)	(4.15)	(6.04)	(5.23)	(4.46)	(4.47)
VOL^{C}_{ATM}		0.001	0.001	0.001		0.001	0.001	0.001
		(3.43)	(3.81)	(3.82)		(5.12)	(4.66)	(4.67)
VOL^{P}_{ATM}		0.001	0.001	0.001		0.001	0.001	0.001
		(4.67)	(3.80)	(3.72)		(1.22)	(1.34)	(1.23)
MOM		0.538	0.643	0.619		1.063	0.905	0.873
		(1.91)	(1.90)	(1.83)		(3.75)	(2.57)	(2.48)
$\mathbf{1}_{HighVola}$			0.022				-0.014	
			(0.39)				(-0.25)	
$OMS^{\sigma}_{t-1} \cdot \mathbf{1}_{HighVola}$			0.319				0.470	
			(1.88)				(2.75)	
$\mathbf{1}_{LowVola}$				-0.030				0.003
				(-0.54)				(0.06)
$OMS^{\sigma}_{t-1} \cdot \mathbf{1}_{LowVola}$				-0.250				-0.38
				(-1.50)				(-2.27)
Adj. R^2	0.014	0.04	0.04	0.035	0.016	0.035	0.034	0.032

of volatility information in the options market prior to macroeconomic announcements. The results also highlight the impact of volatility informed trading on liquidity levels in the options market. In columns (III), (IV), (VII) and (VIII) I investigate whether the volatility state matters to the price impact of the non-announcement day related variation in the OMS^{σ}_{t-1} measure by including dummies and dummy interacted OMS^{σ}_{t-1} measures that condition on high and low volatility states, respectively. In the high volatility case (columns III and VII), the simple macro announcement interacted OMS^{σ}_{t-1} remains significantly positively related with the spreads, and the high vola state interacted OMS^{σ}_{t-1} has a significantly positive coefficient. This implies that in high volatility states, volatility trading predicts a widening of spreads; at non-announcement times, indicated by the coefficient of the non-interacted OMS^{σ}_{t-1} measure, the relationship is negative and significant. On the other hand in the low volatility state (columns (IV) and (VIII)) the interacted OMS^{σ}_{t-1} variable has a significantly negative coefficient while the coefficient for the simple OMS^{σ}_{t-1} becomes even insignificant.

The results imply that volatility trading has a significant impact that decreases options market liquidity levels whenever there is a lot of volatility information trading in the market, hence particularly in high volatility times. When volatility informed investors trade on decreases in the market volatility and the overall level of volatility is not very high, the relationship between the time variation in the volatility informed trading measure and the size of the next day's option spreads is significantly negative.

3.7 Volatility Informed Demand and Investor Uncertainty

The last part of this paper examines the link between volatility informed option demand and investor uncertainty about macroeconomic news. Market volatility, (changes in) volatility risk premia and other second moment related measures are widely associated with investor uncertainty about the economic prospects of an economy.

In particular, high uncertainty about the macro fundamentals is associated with higher stock price volatility on the announcement day because arguably significant news are incorporated in the asset prices on the day of the announcement. Hence, if OMS^{σ} does capture volatility information, I expect it to also predict the uncertainty about macro fundamentals.

A very direct and common way of measuring (ex post) this uncertainty about macro economic fundamentals is the surprise component of macroeconomic forecasts, i.e., the standardized deviation of (the most recent) analyst forecasts from the subsequently announced true realization of the macro variable. Hence, if OMS^{σ} is a significant predictor of the surprise component of macroeconomic fundamentals this implies that OMS^{σ} is useful as an ex ante measure of investor uncertainty on macroeconomic news.

To test the predictive power of OMS^{σ} for investor surprises about macroeconomic news, I first compute the surprise component of the announced macro variable.[25] In accordance with the previous literature (see e.g., Balduzzi et al. 2001, Flannery and Protopapadakis 2002) I use the following standardized measure of macro announcement surprises of announcement type j at time t:

$$Surprise_{t,k} = \frac{A_{t,j} - F_{t,j}}{\sigma_j}, \tag{3.7.1}$$

where $A_{t,j}$ are the at day t announced values of the macro variable j, $F_{t,j}$ are the at time t most recent median forecast values for the macro variable j and σ_j is the unconditional standard deviation of the innovations $A_{t,j} - F_{t,j}$. Obviously, the standardization of $A_{t,j} - F_{t,j}$ is useful to create a surprise measure that is comparable for each macro announcement. Thereafter, I can aggregate the standardized surprise component over all announcement types j and denote the aggregate surprise measure by $Surprise_t$. Since surprises can be of positive or negative sign, I then estimate the following regression using the absolute value of the surprises:

$$|Surprise_t| = \beta_0 + \beta_1 OMS^{\sigma}_{t-1} + \mathbf{bC} + \eta_t, \tag{3.7.2}$$

where

$$\mathbf{C} = \begin{bmatrix} F_t & VOL^C_{t,ATM} & VOL^P_{t,ATM} & MOM_t & I_t \end{bmatrix} \tag{3.7.3}$$

as the vector of control variables.[26] F_t is a standardized measure of analyst forecasts aggregated for all announcement types $j \in$ {CPI, durables, exports, FOMC,...,unemployment}, $VOL^C_{t,ATM}$ and $VOL^P_{t,ATM}$ are ATM call and put volume measures, MOM is a measure that controls for past returns, which might also capture macroeconomic news uncertainty and which I obtain from the daily index return data as cumulative returns of the stock index over a 60 days backward looking window. I is an indicator that is 1 if the announcement was bad news, i.e., stock prices drop on the announcement date, and the indicator is

[25] Note that I exclude observations of two or more announcements within a two day time window because otherwise, it is difficult to identify the effect of an announcement day on OMS^{σ}.

[26] Using only positive or only negative surprises as dependent variable yields qualitatively the same results, which are available on request.

0 otherwise. The intuition for including this term is that in case of bad news, the surprise effect might be different from the effect in case of positive news (e.g., Boyd et al. 2005).

The results for the macro news surprise regressions are reported in Panel A of Table 3.6.

The first specification in Panel A reports the results for regressing the macro news surprises only on OMS^{σ}_{t-1} and the forecast measure. As expected β is positive and significant, i.e., an increase in the level of volatility informed trading correlates with a future increase in the surprise component, showing that OMS^{σ} is also useful as a measure of investor uncertainty on macroeconomic news.

Including the control variables in the second regression model does not change the quality of these results.

As a robustness check, I investigate next whether OMS^{σ} is able to predict or at least explain contemporaneously the true realization of the macro variable. If OMS^{σ} captures volatility information and investor uncertainty on macroeconomic news rather than index return information, the measure should also not capture information about the realized values of the macroeconomic fundamentals; this would require knowledge of the option investors about the future announced value of the macro variable, which should not be the case if OMS^{σ} really captures uncertainty about macroeconomic fundamentals.

To test this, I use in Panel B of Table 3.6 the announced value of the macro variable itself as dependent variable.[27] I start first with using only OMS^{σ}_{t-1} as explanatory variable. In the second regression I also control for and OMS^{σ}_{t} and the forecast value of the macro variable. In the third regression model I include instead $Surprise_t$. The coefficients for OMS^{σ}_{t-1} and also for OMS^{σ}_{t} are insignificant, supporting that OMS^{σ} captures uncertainty about macroeconomic fundamentals rather than information about the actual value of the macro variable.

In Panel C, I additionally investigate whether OMS^{σ} can predict or at least contemporaneously explain the (absolute) first difference of the macro variables. While information about the level could be harder to obtain, the sign and the size of the change might be

[27] In order to make the macro variables comparable, I standardize them.

Table 3.6: **Volatility Trading and Macro Announcements: Further Regression Results.** Panel A reports results for regressions that use the variable $Surprise$ as dependent variable and regress it on OMS^{σ}_{t-1}, $Forecast$ and different controls. Panel B reports results for regressions that use the variable $|\Delta Macrovar.|$ as dependent variable and regress it on OMS^{σ}_{t-1}, OMS^{σ}_{t} and $Forecast$ or $Surprise$. OMS^{σ} is the option demand imbalance measure that is related to volatility informed trading (for details see Section 3.2). F is the last analyst forecast for a respective macro variable before the announcement date. $Macrovar.$ is the standardized value of the macro variable on the announcement date. $|\Delta Macrovar.|$ is the absolute change of $Macrovar.$ on the announcement date. $|Surprise|$ is the absolute value of the unexpected part of the change in the macro variable that is computed as described in Section 3.7. MOM is obtained from the daily return data as cumulative returns of the stock index over a 60 days backward looking window. VOL^{C}_{ATM} and VOL^{P}_{ATM} are the square roots of the daily median ATM call and put option trading volume. I is an indicator that is 1 if the announcement was bad news, i.e., stock prices drop on the announcement date, and the indicator is 0 otherwise. Newey-West robust t-statistics are in parentheses (20 lags). The R^2 is the adjusted R^2. The full sample period is November 2000 to December 2010. The number of observations is 16,207 and 2,537 days with 568 macro announcement days.

Panel A: $|Surprise| = Const. + \beta \times OMS^{\sigma}_{t-1} + \mathbf{B} \times Controls + \eta_t$

$Const.$	OMS^{σ}_{t-1}	F	$VOL^{C}_{t-1,ATM}$	$VOL^{P}_{t-1,ATM}$	MOM	I	$Adj.\ R^2$
-0.81	1.076						0.081
(-8.27)	(3.32)						
0.344	0.701	-0.337	0.001	-0.001	-2.256	-0.076	0.126
(1.03)	(1.70)	(-2.61)	(0.21)	(-1.53)	(-1.58)	(-0.45)	

Panel B: $Macrovar. = Const. + \gamma_1 \times OMS^{\sigma}_{t-1} + \gamma_2 \times OMS^{\sigma}_{t} + \gamma_3 \times \{F \vee Surprise\} + \nu_t$

$Const.$	OMS^{σ}_{t-1}	OMS^{σ}_{t}	F	$Surprise$	$Adj.\ R^2$
1.63	-0.51				0.003
(7.77)	(-0.89)				
0.006	0.055	-0.023	0.836		0.995
(0.46)	(1.41)	(-0.63)	(157.35)		
2.576	-0.037	-0.677		-0.080	0.148
(24.27)	(-0.05)	(-0.86)		(-1.60)	

Panel C: $|\Delta Macrovar.| = Const. + \mu_1 \times OMS^{\sigma}_{t-1} + \mu_2 \times OMS^{\sigma}_{t} + \mu_3 \times \{F \vee Surprise\} + \xi_t$

$Const.$	OMS^{σ}_{t-1}	OMS^{σ}_{t}	F	$Surprise$	$Adj.\ R^2$
0.45	0.22				0.001
(7.57)	(0.93)				
-0.215	-0.173	0.223	0.186		0.002
(-1.05)	(-0.24)	(0.33)	(2.45)		
0.546	-0.582	0.122		0.303	0.116
(4.44)	(-0.85)	(0.19)		(2.72)	

easier to infer.

So in Panel C of Table 3.6, I run the same regressions as in Panel B but now the dependent variable is the aggregate standardized absolute value of the change between the previously announced value of each macro variable j and the value announced at time t.

The results in Panel C reveal that OMS^{σ} neither predicts nor explains the absolute change in the macro variable, which provides further support to the non-directional nature of OMS^{σ} and its arguable benefits as a measure of aggregate uncertainty about macroeconomic news.

3.8 Conclusion

Volatility information in stock index options trading is a relevant but yet understudied research question. This study complements the existing literature by providing evidence for volatility information in stock index option trading. Moreover, the paper highlights that trading on future volatility importantly affects the liquidity in the index options market and is useful to measure uncertainty about macroeconomic fundamentals.

In order to measure volatility informed option demand I use a measure of volatility informed option demand (OMS^{σ}) that is a rolling correlation of the changes in open interest of those contract types that are likely to be used to trade on future volatility (i.e., ATM call and put options with same maturity). The measure predicts future volatility beyond current and lagged realized volatility, the VIX and various other controls. Volatility informed option demand increases prior to macroeconomic announcements. Furthermore, the predictive power of OMS^{σ} for the index volatility increases before macroeconomic news announcements. The results also highlight that volatility informed option demand captures investor uncertainty about macroeconomic news. The effects that I measure are economically significant; trading on volatility informed option demand yields annualized Sharpe Ratios that are up to twice as large as Sharpe Ratios on the corresponding long index investment.

I also investigate the implications of volatility informed trading for liquidity levels in the options market. I find that volatility informed demand increases trigger a widening of spreads in particular before days leading up to macroeconomic announcements. Obviously, market makers are not naive, recognize the volatility information related excess demand patterns and try to protect themselves against future increases in volatility, in particular at times of high aggregate information asymmetry and periods of a higher volatilities informed trading.

Appendices

1 Return Predictive Regressions

As a robustness exercise, I investigate whether OMS^{σ} has any predictive power for future index returns or contains only volatility information as to validate that it is neither directional information nor expected market risk premia or such trading motives that are capture by OMS^{σ}. Furthermore, I also test the return predictive power of OMS^{+} and OMS^{-}. If the measures have no predictive power for index returns this would further support that the index option demand is not driven by directionally informed traders.

The empirical specification of the linear regressions with Newey-West robust standard errors, which I use for the return predictability tests reads as,

$$RET_t = \beta_0 + \beta_1 OMS^{\sigma}_{t-1} + \beta_2 OMS^{+}_{t-1} + \beta_3 OMS^{-}_{t-1} + \mathbf{bC_t} + \epsilon_t, \tag{1.1}$$

with RET_t as the daily S&P500 index return in excess of the risk free rate at day t. β_0, β_1, β_2 and β_3 denote the coefficients of the intercept, OMS^{σ}_{t-1}, OMS^{+}_{t-1} and OMS^{-}_{t-1}. Further, I control in (1.1) for the contemporaneous terms of the volatility and directional OMS measures as well as for the past 60 day average stock returns (MOM), the past 60 day average stock return volatilities (STD) and the daily volume $VOL^{j}_{t,m}$ for $m = \{ATM, ITM, OTM\}$ call or put options, with $j = \{C, P\}$.

Table A1 reports the results for the excess return regressions.

INSERT TABLE A1 ABOUT HERE

I start in column (I) with testing the predictive power of OMS^{σ}. The insignificant coefficient supports that OMS^{σ} indeed captures volatility and not directional information.

Next, column (II) includes also the contemporaneous OMS^{σ} in order to test whether contemporaneously explains returns. The coefficients for the lagged and the contemporaneous OMS^{σ} term are both insignificant, corroborating the result from column (I).

Next, in column (III), I test whether the directional option demand measures, OMS^{+} and OMS^{-}, have predictive power for future returns. The coefficients are insignificant, which is line with the evidence in Pan and Poteshman (2006) that at the index level there is no directional information in option demand.

Similarly to the previous regressions I add in column (IV) also the contemporaneous OMS^{+} and OMS^{-}. The coefficients for the lagged and the contemporaneous OMS^{+} and OMS^{-} measures are all insignificant.

Finally, in column (V) I include all OMS variables and several option and stock index related control variables. The results for the OMS measures remain insignificant.

Table A1: **Regression Results for Daily Realized Stock Index Returns on OMS^{σ} and Controls.** The table provides daily regression results of the daily excess returns of the S&P500 on OMS^{σ} as well as on control variables. The results for some control variables are omitted to save space, however, they are listed and defined below. OMS^{+} and OMS^{-} are options market sidedness measures for the call and the put market, respectively, that are obtained by correlating call and put option contracts (for details see Section 3.2). OMS^{σ} is the option demand imbalance measure that is related to volatility informed trading (for details see Section 3.2). MOM is obtained from the daily return data as cumulative returns of the stock index over a 60 days backward looking window. STD is the average realized standard deviation obtained from the daily returns over a 60 days backward looking window. VOL^{C}_{OTM}, VOL^{C}_{ATM} and VOL^{C}_{ITM} are the daily median call option trading volume that are OTM, ATM or ITM. VOL^{P}_{OTM}, VOL^{P}_{ATM} and VOL^{P}_{ITM} are the daily median put option trading volume that are OTM, ATM or ITM. Newey-West robust t-statistics are in parentheses (20 lags). The R^2 is the adjusted R^2. N is the number of observations. The full sample period is November 2000 to December 2010. The number of observations is 16,207 and 2,537 days.

Excess Return S&P 500	(I)	(II)	(III)	(IV)	(V)
$Const.$	0.013	0.013	-0.032	-0.040	0.085
	(0.61)	(0.60)	(-0.37)	(-0.45)	(0.94)
OMS^{σ}_{t-1}	0.025	-0.023			0.382
	(0.32)	(-0.05)			(0.78)
OMS^{σ}_{t}		0.050			-0.190
		(0.12)			(-0.39)
OMS^{+}_{t-1}			0.040	-0.470	-0.590
			(0.10)	(-0.83)	(-1.07)
OMS^{-}_{t-1}			0.044	-0.004	-0.070
			(-0.15)	(-0.01)	(0.10)
OMS^{+}_{t}				0.521	0.541
				(0.90)	(0.97)
OMS^{-}_{t}				0.053	-0.193
				(0.11)	(-0.41)
MOM					2.853
					(5.56)
STD					-8.504
					(-1.29)
$VOL^{C}_{t-1,OTM}$					-0.000
					(-1.10)
$VOL^{P}_{t-1,OTM}$					0.001
					(0.50)
$VOL^{C}_{t-1,ITM}$					-0.001
					(-1.30)
$VOL^{P}_{t-1,ITM}$					0.001
					(1.47)
$VOL^{C}_{t-1,ATM}$					-0.000
					(-1.36)
$VOL^{P}_{t-1,ATM}$					0.000
					(3.75)
Adj. R^2	-0.001	-0.001	-0.001	0.001	0.033
N	2,537	2,537	2,537	2,537	2,537

Chapter 4

Financing Asset Sales and Business Cycles

joint with Marc Arnold and Dirk Hackbarth

4.1 Introduction

A crucial component of corporate investment decisions is the choice of the source of funding. In practice, asset sales play an important role for investment financing. For instance in 2011, the French cement giant Lafarge targeted EUR 750 million (USD 1.1 billion) of asset sales to refinance parts of its debt for the 2007 purchase of Egyptian Orascom Cement. In the same year, Thomson Reuter's announced to raise about USD 1 billion by selling two businesses to fund further investments. In fall 2012, Petrobras announced large asset sales to contribute to the financing needs of nearly USD 15 billion to fund its five-year investment plan. While debt and equity are widely studied sources of investment financing, asset sales are rarely considered. This is surprising, given that the average amount of asset sales corresponds to roughly 44% of the average amount of newly issued equity for U.S. manufacturing firms in Compustat between 1971 and 2010.

This paper analyzes the decision of firms to sell assets to fund investments (financing asset sales). We uncover a novel aspect of this decision, that is, the relation between financing asset sales and the well-known debt overhang problem (Myers 1977). We show that this relation explains stylized facts of empirically observed asset sale patterns. Recognizing that future investment may be financed with asset sales also has important consequences for corporate investment policy, and firm valuation. Furthermore, our study features original insights on the amplification effects of real business cycle shocks on investment and asset sale decisions of firms. We incorporate business cycles in our analysis for two reasons. First, while the cyclicality of external financing is intensively studied in recent papers, the cyclicality of financing asset sales is not discussed (e.g. Korajczyk and Levy 2003) . Second, previous work finds that business cyclicality is crucial to understand financing and investment decisions (e.g., Chen and Manso 2010).

We document empirical facts for a sample of U.S. manufacturing firms that cannot jointly be explained with traditional motivations for asset sales, such as financial distress or financial constraints.[1] As the incentive for asset sales is unobservable in our data, we focus on the correlation between asset sales and investment. The idea behind this approach is that financing asset sales should be reflected in the correlation between asset sales and investment. We explore firm-specific and business cycle related variables that drive this correlation to draw conclusions about the main determinants of financing asset sales. At the same time, the regression set-up allows us to control for other firm and industry characteristics that are potentially correlated with asset sales. We find that the correlation between asset sales and investment is significantly higher (i) for firms with higher leverage, (ii) in bad business cycle states, (iii) for firms with a low cyclicality of growth options in bad business cycle states, and (iv) for unconstrained firms.

Motivated by these stylized facts on financing asset sales, we derive the implications of a structural model with intertemporal macroeconomic risk, embedded inside a representative agent consumption-based asset pricing framework in the spirit of Bhamra et al. (2010b) and Chen (2010). To generate financing needs, our model firms do not only consist of invested assets but, following Arnold et al. (2013), also have a growth option that is costly to exercise. We augment this model environment by incorporating business cycle dependency of the equity issuance cost, the asset liquidity, and the growth option. Moreover, the structural model approach allows us to relate financing asset sales to the debt overhang (i.e., wealth transfer) problem between equityholders and debtholders by analyzing equityholders' endogenous choice between issuing new equity and selling assets to finance the exercise of the growth option. The consumption-based asset pricing frame-

[1] See for instance, Shleifer and Vishny (1992) or Weiss and Wruck (1998) for papers that relate asset sales to corporate distress and, for instance, Lang et al. (1995), Hovakimian and Titman (2006), Bates (2005) for papers that highlight the role of asset sales as source of investment financing for constrained firms.

work determines how aggregate risk and risk prices change with the business cycle. It features a representative agent whose utility incorporates both, time and state preferences (e.g. Duffie and Epstein 1992a, Duffie and Epstein 1992b). The agent's preference for an early resolution of uncertainty affects the stochastic discount factor and, hence, has an impact on security prices. The changes between good and bad business cycle states are driven by an observable Markov chain. This asset pricing approach directly links financing asset sale decisions to asset prices and economic fundamentals.

Our analysis starts with a typical firm at initiation that consists of assets in place and a growth option. It is initially financed with equity and risky debt. When the firm exercises its growth option, the total asset volatility decreases, and total earnings increase. Hence, the exercise creates a wealth transfer from equityholders to debtholders because debt becomes less risky. Due to this agency problem, equityholders invest too late compared to an investment policy that maximizes the value of the expansion option (underinvestment).

Equityholders decide whether to fund the exercise cost of the growth option by issuing equity or by selling assets. Selling assets when exercising the option increases leverage, which renders debt more risky. The increase in the riskiness of debt associated with the asset sale causes a reverse wealth transfer from debtholders to equityholders that mitigates the wealth transfer problem. As a consequence, asset sales are relatively more attractive to equityholders of firms that are more exposed to the wealth transfer problem.

The wealth transfer problem is larger for more leveraged firms (see e.g. Myers 1977) because debt is riskier and, hence, more sensitive to earnings and asset volatility changes. As a consequence, equityholders of more leveraged firms have a stronger incentive to use financing asset sales. This insight provides a compelling explanation to our first stylized fact that the correlation between asset sales and investment is significantly higher for firms with larger leverage. Moreover, our model allows us to examine the endogenous relation between business cycles and financing asset sales. In bad business cycle states, leverage increases for a given level of earnings because the decrease in the asset value of a firm is larger than the decrease in the debt value. At the same time, however, equityholders optimally invest at a higher earnings level than in good business cycle states, which induces a lower leverage at investment. Our results show that the first effect dominates, i.e., leverage at investment is higher in bad business cycle states. Since the wealth transfer problem at option exercise is larger for higher levels of leverage, our model predicts that equityholders tend to prefer financing asset sales during bad business cycle states. This finding provides an explanation to our second stylized fact, i.e., to the increased correlation between asset sales and investment in bad states. Finally, the model also shows why firms with a less cyclical growth option tend to use more financing asset sales, conditional on investing in bad states. The more valuable a firm's growth option is in bad states, the lower is the earnings level at which it optimally invests during bad states. A lower earnings threshold for investment entails a higher leverage at investment. For a higher leverage, the wealth transfer problem is more pronounced, which implies that equityholders have a higher incentive to use financing asset sales during bad states.

To explore the dynamic features of our model, we simulate panels of model-implied firms that are structurally similar to the Compustat sample. Each simulation generates a time series of investment, financing, and default observations over the business cycles. We compare these simulated observations to the empirical patterns to validate the model. The model-implied dynamic patterns of financing asset sales provide an explanation to the stylized facts on asset sales and investments that we document in our empirical analysis. In particular, we find that, on average, 39% of the investments in our simulations are financed with asset sales. The simulated samples match our empirical finding (i) that the correlation between asset sales and investment rises with leverage. The number of firms that use financing asset sales conditional on investment increases to roughly 52% for firms in the highest leverage tercile compared to 35% in the lowest tercile. Investment and financing asset sales in the simulated samples are procyclical, and often peak at those points in time at which the economy switches from a bad to a good state. The fraction of firms that use financing asset sales to invest increases to 44% during bad states, and decreases to 36% during good states, which reflects our empirical finding (ii) that the correlation between asset sales and investment is higher in bad business cycle states. Finally, we also match our empirical prediction (iii). The cyclicality of the growth opportunity is important in that the fraction of firms that use financing asset sales to invest during bad states in the simulated samples is particularly large for the subsample of firms that have a less cyclical growth option. In sum, the simulation results show that our model, in which the wealth transfer problem drives the decision of firms to sell assets, yields dynamic patterns of financing asset sales that explain the stylized facts in the Compustat data.

Our contribution is three-fold. First, we develop a dynamic model of investment and financing that endogenizes the choice between equity and asset sales as funding source and yields a set of novel insights and testable predictions that improve our understanding about asset sale motives of firms.[2] That is, we provide theoretical and empirical evidence for agency conflicts between debt and equity as an important and heretofore neglected motive for asset sales. Our findings complement previous work that associates asset sales with alternative motives. Weiss and Wruck (1998), Hovakimian and Titman (2006), and Bates (2005), for example, discuss investment funding needs of financially constrained or distressed firms as a reason for asset sales. Warusawitharana (2008) argues that asset reallocations are mainly driven by firm-specific productivity shocks. More recently, Edmans and Mann (2013) revisit the pecking order theory by examining the relative information asymmetry associated with equity issuance and asset sales. Lang et al. (1995), and Bates (2005) focus on the tradeoff between investment efficiency and agency costs of managerial discretion associated with selling assets. Morellec (2001) is the only paper that also considers agency conflicts between debt and equity in the context of asset sales. He highlights that asset liquidity increases the debt capacity only when bond covenants restrict the disposition of assets close to bankruptcy. In contrast, we model asset sales to finance investment and show that it is optimal for equityholders to negotiate debt covenants that admit asset sales if their proceeds are used to purchase new assets.

Second, we contribute to a line of research that emphasizes the importance of cyclicality for capital structure and credit risk (see e.g. Hackbarth et al. 2006). We show that incorporating the impact of business cycle shocks is crucial to jointly explain the corporate investment and financing asset sale decisions. While the effect of cyclicality

[2] Equityholders' choice between issuing equity and selling assets upon investment is a first step towards understanding financing asset sales. A second step could be to consider more funding sources, such as debt. Incorporating optimal debt restructuring upon investment yields a very large leverage choice because equityholders do not incorporate the bankruptcy costs imposed by the new debt on initial debtholders. This distortion would drive the investment and asset sale decisions of firms. Note that the problem can not be solved by implementing a priority structure as suggested in Hackbarth and Mauer (2012) for a one regime model. The reason is that, at initiation, it is not known at which threshold the growth option will be exercised in our two regime model. A framework with initial debt renegotiation is needed to address the problem, which is beyond the scope of this paper.

on asset sales through the productivity channel is already explored (e.g. Maksimovic and Phillips 2001, Yang 2008), the impact of cyclicality through the financing channel has so far been neglected. A closely related paper that considers macroeconomic risk and the debt overhang problem is Chen and Manso (2010). Their results emphasize the cyclical nature of growth opportunities, and the increase of debt overhang in bad states. However, they do not consider the role of asset sales. Our findings on the cyclical nature of financing asset sales also complement the empirical literature that suggests internal resources are more important during worse economic times (e.g., Duchin et al. 2010, Lemmon and Roberts 2010, Campbello et al. 2010, Campello et al. 2011).

Third, this paper integrates to a growing literature in corporate finance that uses simulated panels based on structural models to explain stylized facts in real firm data (see e.g., Gomes and Livdan 2004, Hennessy and Whited 2007, Strebulaev 2007). As endogeneity problems are hard to resolve with an appropriate empirical identification strategy, we use our structural model to rationalize and support the stylized patterns about the relation between financing asset sales and investments that we observe in the real data.

The paper proceeds as follow. In Section 4.2, we establish empirical facts on the correlation between asset sales and investment. Section 4.3 introduces a structural model that to explain these stylized facts. Section 4.4 presents the model solution, and Section 4.5 derives the predictions generated by our model for a typical firm at initiation. Finally, we simulate model-implied economies of firms to analyze the aggregate dynamics of financing asset sales in Section 4.6. Section 4.7 concludes.

4.2 Stylized Facts

In this section, we document empirical patterns for a sample of U.S. manufacturing firms. In particular, we show that business cycle conditions, corporate investments, and time-variation of growth opportunities are key determinants of financing asset sales.[3] The data on asset sales (Compustat item SPPE) does not reveal the motive behind the asset sales. We can also not exploit a (quasi-) natural experiment or a discontinuity. Hence, we try to identify firm characteristics and business cycle related factors that increase the correlation

[3] The sample period is 1971 to 2010. The final sample consists of 3,592 firms in Compustat. All variable definitions, data cleaning filters and summary statistics for the sample are provided in 2.

between asset sales and investment. The idea behind this approach is that more financing asset sales should result in an increased correlation between contemporaneous investment and asset sale. Moreover, focusing on this correlation allows us to abstract away from fire sales of financially distressed firms. The reason is that it is unlikely that distressed firms tend to invest heavily in those periods, in which they are forced to sell assets to repay their debt (e.g., Shleifer and Vishny 1992). We document that the correlation between asset sales and investments is higher (i) for firms with higher leverage, (ii) in bad business cycle states, (iii) for firms with less cyclical growth opportunities in bad business cycle states, and (iv) for unconstrained firms.

Table 4.1 reports results for OLS panel regressions that explore the correlation of asset sales with investment, leverage, the cyclicality of a firm's growth opportunities, financial constraints and other controls for various firm characteristics. We include industry fixed effects. The standard errors are autocorrelation robust and clustered at the industry level, and the R^2s are adjusted for the number of variables in the regression.[4]

In column (I), we investigate the relationship of asset sale with investment using growth opportunities (q), measures of financial flexibility (cash flow and financial slack), and financial leverage as controls. The regression coefficient of investment shows that asset sale and investment are highly significantly and positively correlated. Lagged cash flows and q exhibit a negative significant regression coefficient, while lagged financial slack and coverage ratio are not significantly correlated with asset sale. The positive significant association of asset sale and investment suggests that financing asset sales are a potential source of investment funding. However, we cannot interpret this correlation by itself as an indicator of whether the wealth transfer problem between equityholders and debtholders is a potential motive for firms to use financing asset sales.

To explore this question, we first investigate factors known to be related to the wealth transfer problem that potentially increase the correlation between investments and asset sales. For instance, the wealth transfer problem increases with firm leverage (see e.g. Myers 1977). Hence, in column (II), we explore the role of leverage for the relationship between asset sale and investment using an interaction term of investment and leverage.

[4]The quality of our results remains unaffected if we use, e.g., two-step GMM estimations or two-way clustering at the year and at the industry level or alternatively at the year and at the firm level.

Table 4.1: **Compustat Sample Asset Sale Determinants**

The table reports parameter estimates for industry-fixed effect linear regressions and industry-clustered autocorrelation robust t-statistics (in parentheses) with *Asset Sale* as dependent variable. *Asset Sale* are the cash proceeds from the sale of fixed capital. *Investment* is equal to capital expenditures. *Cash flow* is the first lag of the sum of income before extraordinary items and depreciation and amortization. q is the first lag of the sum of the book value of total debt and market value equity divided by the book value of total assets. *Leverage* is the first lag of (LT+PSTK-TXDB-DCVT). *Financial Slack* is the first lag of the sum of cash and short-term investments. *Investment*, *Cash Flow*, *Asset Sale*, and *Financial Slack* are scaled by the book value of the beginning-of-period net fixed assets. The variable *Cov. Ratio* is the first lag of the ratio of $EBITDA$ divided by the interest expenses. $Corr(q, Salesgr.)$ is the firm individual 5-year rolling correlation of the firm individual q with the aggregate annual sales growth across all firms. *SA Index* is the first lag of the SA-Index that is computed as $-0.737 * Total\ Assets + 0.043 * (Total\ Assets)^2 - 0.04 * Age$. Since the SA-index exhibits very high values by construction, we scale the variable with 10×10^7. *Bad State* is a dummy that is one if the aggregate sales growth and the average annual equity return across all firms in the sample are, simultaneously, in the bottom 25% of all years. $\mathrm{I}_{Low\ Z}$ is a dummy that is one if a firm has a Z-Score (see Equation (B.2)) value below 3. The sample period is 1971 to 2010. N is the number of observations in the corresponding regression. The full sample consists of an unbalanced sample of 3563 U.S. manufacturing firms.

Dependent variable: Asset sale	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Investment	0.020	0.003	0.019	0.022	0.020	0.020	0.003	0.020	0.005
	(4.34)	(0.35)	(4.02)	(4.99)	(4.29)	(4.27)	(0.47)	(4.28)	(0.94)
Cash Flow	-0.002	-0.002	-0.002	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002
	(-5.79)	(-6.01)	(-5.80)	(-5.33)	(-5.82)	(-5.76)	(-5.96)	(-5.80)	(-5.93)
q	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-21.83)	(-20.23)	(-21.89)	(-19.87)	(-22.55)	(-22.76)	(-20.17)	(-18.14)	(-16.72)
Financial Slack	-0.000	0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	0.000
	(-0.47)	(0.36)	(-0.45)	(1.34)	(-0.52)	(-0.51)	(0.29)	(-0.79)	(0.00)
Cov. Ratio	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.27)	(-1.07)	(-1.25)	(-0.97)	(-1.29)	(-1.29)	(-1.11)	(-2.70)	(-2.71)
Leverage	0.012	0.004	0.012	0.012	0.012	0.012	0.004	0.012	0.004
	(3.27)	(0.89)	(3.25)	(3.13)	(3.20)	(3.21)	(0.96)	(3.37)	(0.97)
Lever. x Invest.		0.043					0.040		0.036
		(2.91)					(2.76)		(3.00)
Bad State x Invest.			0.014	0.019					
			(2.68)	(2.25)					
Bad State			-0.004	-0.006					
			(-3.89)	(-3.90)					
Corr(q,Salesgr.)				0.001					
				(0.96)					
Invest. x Corr(q,Salesgr.)				-0.001					
				(-0.38)					
Bad State x Corr(q,Salesgr.)				0.005					
				(2.26)					
Invest. x Bad State x Corr(q,Salesgr.)				-0.024					
				(-2.35)					
SA-Index					0.009	-0.005	0.040		
					(7.94)	(-1.03)	(1.05)		
Invest. x SA-Index						0.043	-0.298		
						(2.66)	(-3.81)		
Lever. x SA-Index							-0.068		
							(-1.05)		
Invest. x Lever. x SA-Index							0.548		
							(4.08)		
$\mathrm{I}_{Low\ Z}$								0.000	0.000
								(1.77)	(1.43)
Invest. x $\mathrm{I}_{Low\ Z}$								0.007	-0.001
								(1.35)	(-0.07)
Lever. x $\mathrm{I}_{Low\ Z}$									0.001
									(0.39)
Invest. x Lever. x $\mathrm{I}_{Low\ Z}$									0.011
									(0.37)
Industry-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.031	0.032	0.032	0.032	0.032	0.033	0.034	0.032	0.033
No. of Obs.	24277	24277	24277	19807	24277	24277	24277	23972	23972

If a higher leverage affects the relation between asset sales and investment, we expect a positive coefficient for the interaction term. The result in column (II) confirms that the correlation between asset sales and investment increases with leverage.

Moreover, the simple investment and leverage coefficients become insignificant when we add an interaction term between investment and leverage.[5]

Chen and Manso (2010) show that the wealth transfer problem is more severe in bad states of the business cycle. Hence, we are interested in how the correlation between asset sale and investment is related to macroeconomic conditions. In column (III) of Table 4.1, we incorporate in our first baseline regression the interaction between the investment variable and a dummy that is equal to one in a bad business cycle states of our sample economy.[6] The positive coefficient on this interaction term shows that the correlation between investment and asset sales is higher in business cycle downturns. This finding emphasizes the importance of recognizing business cycle dynamics when explaining the positive correlation of investment and asset sale.

To further explore the role of cyclicality for financing asset sales, we now investigate whether firms, that have relatively valuable growth opportunities in bad states of the business cycle, exhibit an increased correlation between asset sales and investment during bad states. Chen and Manso (2010) demonstrate that a firm's exposure to the wealth transfer problem is linked to the cyclicality of its growth option. Therefore, we next test whether we can link financing asset sales to the cyclicality of growth opportunities. To this end, we add in column (IV) an interaction term that is the product of three variables. The first one is investment, the second one is a dummy that is equal to one if the sample economy is in a bad state and zero otherwise, and the third one corresponds to the correlation between a firm's growth opportunity and the aggregate business cycle state. To construct the correlation measure, we estimate 5-year rolling window correlations between the firm individual q and the aggregate sales growth in our entire sample.[7] The intuition

[5] In unreported regressions, we also control for debt issuance. We find that debt issuance has no impact on our qualitative results regarding the asset sale and investment correlation. The results are available from the authors upon request.

[6] A year is defined as a bad business cycle year if the sample aggregate sales growth and the average annual equity return across sample firms are, simultaneously, in the bottom 25% of all years. We choose this definition of a business cycle downturn because sales growth combined with market based downturn measures are a direct measure of the propagation of positive and negative shocks from the aggregate economy onto the corporate level (see also the downturn definitions in, e.g., Opler and Titman 1994, Gilson et al. 1990). Estimating a trend model of aggregate sales growth, similar to McQueen and Roley (1993b), provides qualitatively similar results.

[7] We scale the firm individual q by the SIC3-industry average q to control for industry effects. To test the robustness, we also use specifications in the spirit of the industry downturn definition in, e.g., Opler and Titman (1994) or Gilson et al. (1990), whereat we correlate q with sales growth that is aggregated

for this measure is that firms with a relatively lower correlation tend to exhibit relatively more valuable growth opportunities in the bad state of the business cycle, while high correlation firms have more cyclical growth opportunities.[8] We find a negative coefficient for the interaction term between investment, business cycle state and the cyclicality of a firm's growth opportunity, implying that in bad states of the business cycle, firms with a relatively lower cyclicality exhibit a stronger relationship between investments and asset sales. Notably, the significance of the positive investment coefficient is not wiped out after including the interaction term in column (IV), only the size of the coefficient decreases.

The above results indicate along several dimensions that the correlation between asset sales and investment increases with firm characteristics that the literature directly links to an increased wealth transfer problem. An alternative explanation could be that the positive relationship of leverage to the correlation between asset sales and investments is caused by external financing constraints (e.g. Lang et al. 1995, Hovakimian and Titman 2006, Bates 2005). To analyze the potential role of financing constraints for the correlation between asset sales and investment, we add in column (V) the SA-index as a proxy for financial (un)constraints of a firm.[9] The coefficient is positive and highly significant, implying that firm size and age contribute to an increasing variation in asset sales.[10] Yet, the result does not answer the question whether financial constraints are an important driver of the relationship between investments and asset sales. Therefore, we incorporate the interaction of the SA-index with investment as an additional independent variable in column

at the SIC2-industry level, and find qualitatively similar results. Moreover, we use larger windows for the correlation measure (e.g., seven years) without qualitatively affecting the results.

[8]The 25% quantile of the correlation distribution for all firms is -0.5, the median is 0.02, and the 75% quantile is 0.56.

[9]According to Hadlock and Pierce (2010), the SA-index is useful to measure the financial constraints of a firm. Related work supports the view that the ingredients of this index, i.e., size and age, capture the financial constrainedness of a firm (see e.g. Hennessy and Whited 2007, Fee et al. 2009). Furthermore, size and age are also often interpreted as information asymmetry measures (see e.g. Leary and Roberts 2010).

[10]Note that the magnitude of the coefficient is a matter of scaling. Since the SA-index is a combination of total assets, squared total assets and age, its values are substantially higher than the values of asset sales, which is a variable that is scaled with total assets. Therefore, we scale the SA-index by 10×10^7. If we sort firms each year according to their SA-index values and interact investment with dummies that are one if a firm is in the lowest or highest SA-index tercile, respectively, and zero otherwise, we find a significant increase in the investment and asset sale relation for firms in the high SA-index group, and an insignificant relation for firms in the low group. Moreover, the size of the coefficient for the high SA-index group is comparable to the coefficients of the investment and leverage interaction in column (II). However, because this approach requires to omit one third of our data, we prefer to present the results of the full sample by directly using the SA-index as a scaling term.

(VI). The interaction term is positive and significant, suggesting that unconstrained rather than constrained firms exhibit a stronger relationship between investment and asset sales.

Next, we conduct another test of the question whether the increase in the asset sale and investment correlation for higher leverage firms is indeed likely to be related to the wealth transfer problem. For this purpose, we also incorporate the firm individual level of financial constraints into our analysis. It is well-known that less financially constrained firms have a higher debt capacity, i.e., they can lever up their firm more easily (e.g. Kiyotaki and Moore 1997, Almeida and Campello 2007, Hahn and Lee 2012, Hart and Moore 1994). Put differently, debt overhang is not an agency problem that relates to financial constraints, because it is more relevant for firms that are relatively unconstrained and can take on high leverage. Therefore, we include in column (VII) an interaction term that scales investment with both variables, leverage and the SA-index. If our hypotheses on the relation between financing asset sales and the wealth transfer problem are correct, then the coefficient of this term should be positive and significant, indicating that for firms that are less financially constrained the correlation between asset sales and investment increases with leverage. The positive significant coefficient for the interaction term supports our view. Notably, once we control for the effect of leverage, the interaction of investment and the SA-index switches sign. Thus, higher leverage and, therefore, supposedly the wealth transfer problem is the driving force of the increased correlation between asset sales and investments for more unconstrained firms.

We argue that an increase in the correlation between asset sales and investments reflects an increase in financing asset sales rather than asset sales by financially distressed firms that need to repay debt, i.e., fire sales (e.g. Shleifer and Vishny 1992, Weiss and Wruck 1998, Lang et al. 1995). To validate our hypothesis, we test in the final regression models whether financial distress has an impact on the correlation between asset sales and investment. We do so by including in column (VIII) an interaction term of investment and a dummy that indicates if the firm individual Altman (1968) Z-score is below a value of three, i.e., indicates that the firm is likely to be financially distressed. If financial distress were a driver of the asset sale and investment correlation, we would expect a positive significant coefficient for the interaction term. However, the regression results reveal an insignificant coefficient for the interaction term. This finding supports our view that an increase in the correlation between asset sales and investment is likely to be related to financing asset sales rather than to fire sales.

Finally, the results for the interaction between investment and leverage could also be driven by financial distress. To address this concern, we include a new interaction term of investment, leverage, and the Z-score dummy in column (IX). If financial distress were to matter for the coefficient on the interaction between investment and leverage, we would expect a positive coefficient on this new interaction term. However, the coefficient is insignificant, and the interaction between investment and leverage by itself is hardly affected (compared to column II) if we include the new interaction term. Thus, this establishes that financial distress is not the driver of the positive impact of leverage on the correlation between investment and asset sales.

To summarize, we illustrate novel stylized facts for the correlation between investments and asset sales that cannot be explained by traditional motives for asset sales, such as financial constraints or financial distress. Our regressions indicate that leverage, rather than proxies for financial constraints or financial distress, drives the correlation between investments and asset sales. We interpret our results as evidence that the well-known wealth transfer problem is an important driver of financing asset sales.

4.3 Model setup

In this section, we study a structural model with time-varying macroeconomic conditions, embedded inside a representative agent consumption-based asset pricing framework in the spirit of Bhamra et al. (2010b) and Chen (2010). This framework determines how aggregate risk and risk prices change with the business cycle. It links the fluctuations in the first and second moments of aggregate growth rates to the valuation of corporate securities. It is well suited to explore the role of financing asset sales over the business cycles, as it allows us to endogenize the effect of cyclicality in a simple and realistic fashion. Moreover, it shows how the values of equity, debt, and growth options that determine firms' external financing decisions are endogenously affected by time-varying business cycle conditions.

Following Arnold et al. (2013), each firm has one growth option that is costly to exercise. The key innovation in our paper is that we allow firms to endogenously choose between financing the investment cost with the proceeds from the asset sales or the issuance of new equity. Moreover, we incorporate business cycle dependent equity issuance cost, asset liquidity, and cyclicality of the growth option. The structural model approach allows us to analyze equityholders' endogenous choice between issuing new equity and selling assets to finance the exercise of the growth option in an economy with external financing frictions. In addition, it easily lends itself to analyzing firm behavior in simulated panels.

A potential caveat for financing asset sales is the existence of covenants in credit contracts that could restrict both investment and this source of internal financing. The covenant literature, however, suggests that observed covenants provide firms with substantial flexibility to invest in expanding the business activities, and with respect to the required investment financing with new equity or asset sales.[11]

4.3.1 Firm Earnings, Investment Financing and Time-Varying Business Cycle Conditions

The economy consists of N different firms with assets in place and a growth option, a large number of identical infinitely lived households, and a government serving as a tax authority. There are two different aggregate states, namely, good (G) and bad (B) states. Aggregate output, corporate earnings, and external financing frictions depend on the current state. To model time-varying aggregate conditions, we define a time-homogeneous observable Markov chain $I_{t\geq 0}$ with state space $\{G, B\}$ and generator $Q := \left[\begin{smallmatrix} -\lambda_G & \lambda_G \\ \lambda_B & -\lambda_B \end{smallmatrix}\right]$, in which $\lambda_i \in (0,1)$ is the rate of leaving state i.

[11] Nini et al. (2009) provide evidence of a widespread use of covenants that restrict investments in private credit agreements. Their results, however, suggest that capital expenditure covenants address asset substitution and fire sales rather than investments in growth opportunities. In particular, the authors find that capital expenditure restrictions are less likely in credit agreements of firms with more favorable investment opportunities. They also show that banks and borrowers tend to leave the investment policy unrestricted when credit quality is high, or as long as covenants are not violated. Chava et al. (2009) show that bond covenants that restrict stock issuance are relatively rare compared to covenants that restrict the issuance of debt. While covenants on asset sales are frequently used, they often explicitly allow firms to sell assets in the ordinary course of business, or as long as the proceeds from the asset sale are used to purchase new fixed assets (Smith and Warner 1979). Another common practice in asset covenants of private corporate debt contracts is to restrict asset disposition only above a certain fixed amount (Bradley and Roberts 2004).

The aggregate output C_t follows a regime-switching geometric Brownian motion

$$\frac{\mathrm{d}C_t}{C_t} = \theta_i \mathrm{d}t + \sigma_i^C \mathrm{d}W_t^C,\ i = G, B, \tag{4.3.1}$$

in which W_t^C is a Brownian motion independent of the Markov chain. The parameters θ_i and σ_i^C are the growth rates and volatilities of the aggregate output, respectively. To incorporate the impact of time-varying aggregate conditions, they are both regime-dependent. In equilibrium, aggregate consumption equals aggregate output. The representative agent has the continuous-time analog of Epstein-Zin-Weil preferences of stochastic differential utility type (e.g. Duffie and Epstein 1992a, Duffie and Epstein 1992b). The dynamics of the stochastic discount factor, the risk-free rates, r_i, the market prices of consumption risk, η_i, and the market prices of jump risk, κ_i, are derived in 1.1.

At any time, the earnings process of a firm follows

$$\frac{\mathrm{d}X_t}{X_t} = \mu_i \mathrm{d}t + \sigma_i^{X,C} \mathrm{d}W_t^C + \sigma^{X,id} \mathrm{d}W_t^X, \quad i = G, B, \tag{4.3.2}$$

in which W_t^X is a standard Brownian motion describing an idiosyncratic shock, independent of the aggregate output shock W_t^C and the Markov chain. μ_i are the regime-dependent drifts; $\sigma_i^{X,C} > 0$, the firm-specific regime-dependent volatilities associated with the aggregate output process; and $\sigma^{X,id} > 0$, the firm-specific volatility associated with the idiosyncratic Brownian shock.

Denote the risk-neutral measure by $\mathbb{Q}$. The expected growth rates, $\tilde{\mu}_i$, of a firm's earnings under the risk-neutral measure are given by

$$\tilde{\mu}_i := \mu_i - \sigma_i^{X,C} \eta_i, \tag{4.3.3}$$

and the risk-neutral transition intensities, $\tilde{\lambda}_i$, by

$$\tilde{\lambda}_i = e^{\kappa_i} \lambda_i. \tag{4.3.4}$$

Intuitively, in bad times when marginal utility is higher, bad news about future earnings are worse. Hence, by incorporating jump-risk into the expression in Equation (4.3.4), we link the historical probabilities of a change in the regime with the risk-neutral probabilities. The main effect for the security prices is that, under the risk neutral measure, bad states last longer and the economy switches faster from a good to a bad state.

Corporate taxes need to be paid at a constant rate τ, and full offsets of corporate losses are allowed. Following Hackbarth et al. (2006), Chen (2010), and Bhamra et al. (2010b), the unleveraged after-tax asset value of a firm can then be written as

$$V_t = (1-\tau) X_t y_i, \quad i = G, B, \tag{4.3.5}$$

with y_i being the price-earnings ratio in state i determined by

$$y_i^{-1} = r_i - \tilde{\mu}_i + \frac{(r_i - \tilde{\mu}_j) - (r_i - \tilde{\mu}_i)}{r_j - \tilde{\mu}_j + \tilde{p}} \tilde{p} \tilde{f}_j. \tag{4.3.6}$$

$\tilde{p} := \tilde{\lambda}_i + \tilde{\lambda}_j$ is the risk-neutral rate of news arrival, and $\left(\tilde{f}_G, \tilde{f}_B\right) = \left(\frac{\lambda_B}{\tilde{p}}, \frac{\lambda_G}{\tilde{p}}\right)$ is the long-run risk-neutral distribution. y^{-1} can be interpreted as a discount rate, in which the first two terms constitute the standard expression if the economy stayed in regime i forever, and the last term accounts for future time spent in regime j. As in Bhamra et al. (2010b), the price-earnings ratio in the main analysis is higher in good states than in bad states, i.e., $y_G > y_B$.

Finally, the volatility of the earnings process in regime i can be expressed as

$$\bar{\sigma}_i = \sqrt{\left(\sigma_i^{X,C}\right)^2 + \left(\sigma^{X,id}\right)^2}. \tag{4.3.7}$$

A firm's expansion (growth) option is modeled as an American call option on its earnings. In particular, a firm (i) can irreversibly exercise this option at any time $\bar{t}$, (ii) needs to pay the exercise cost $K_{\bar{i}}$, and (iii) achieves additional future earnings of $s_{\bar{i}} X_t$ for all $t \geq \bar{t}$ for some factor $s_{\bar{i}} > 0$, in which $\bar{i}$ is the realized state of the economy at the time of exercise. In contrast to Arnold et al. (2013), both the exercise cost $K_{\bar{i}}$ and the factor $s_{\bar{i}}$ are regime-dependent to model firms with varying degrees of the cyclicality of their growth option. If an expansion option is exercised, it is once and for all converted into assets in place, so the firm consists of only invested assets.

A firm can finance the exercise cost $K_{\bar{i}}$ of the expansion option by either issuing new equity or by selling assets in place. As suggested by the literature (e.g. Campello and Hackbarth 2012), we explicitly incorporate external financing frictions, i.e., that new equity financing is costly. In particular, each equity-financed \$1 leads to a regime-dependent issue cost of $\Upsilon_{\bar{i}}$. The regime dependency of Υ_i allows us to capture the notion that external equity financing is more restricted during bad states (e.g. Erel et al. 2011). The cost Υ_i can be interpreted as the linear component of the equity issuance cost. Hence, a firm with access to equity financing in a given regime can finance the exercise cost $K_{\bar{i}}$ by issuing new equity of $K_{\bar{i}}(1+\Upsilon_{\bar{i}})$.

Pulvino (1998) and Jovanovic and Rousseau (2002) argue that selling assets is costly. The cost occurs because assets are partially firm-specific and the firm-specific component is irreversibly lost in asset transfers, or because existing assets are not made-to-order and, therefore, may require additional disassembling costs to tailor the assets to the buyer's specific needs. We incorporate this friction by stating that the proceeds from selling assets on the market correspond to $0 \leq \Lambda_i \leq 1$ times the value of the assets to the firm. Consistent with Shleifer and Vishny (1992), the parameter Λ_i can be interpreted as the regime-dependent liquidity of the firm's assets in place, and is calibrated such that $\Lambda_G > \Lambda_B$. After exercising the expansion option, the firm obtains current earnings of $(s_{\bar{i}}+1)X_t$, i.e., $s_{\bar{i}}X_t$ from the expansion option, and X_t from existing assets in place. The value of the existing assets in place at option exercise corresponds to $(1-\tau)X_{\bar{t}}y_{\bar{i}}$. The value of the assets required to be sold to finance the exercise cost of the expansion option is given by $K_{\bar{i}}/\Lambda_{\bar{i}}$. Hence, the fraction $\frac{K_{\bar{i}}/\Lambda_{\bar{i}}}{(1-\tau)X_{\bar{t}}y_{\bar{i}}}$ of current earnings needs to be sold to finance the option exercise. As a result, total earnings of a firm at any point in time after financing the exercise cost by selling assets correspond to

$$\left(s_{\bar{i}} + 1 - \frac{K_{\bar{i}}/\Lambda_{\bar{i}}}{(1-\tau)X_{\bar{t}}y_{\bar{i}}}\right) X_t. \tag{4.3.8}$$

Firms take on (risky) debt because it allows them to shield part of the corporate income from taxation. The debt maturity is assumed to be infinite. Once debt has been issued, a firm pays a coupon c at each moment in time. Shareholders have the option to default on their debt obligations. Default is triggered when shareholders are no longer willing to inject additional equity capital to meet net debt service requirements (e.g. Leland 1998). If default occurs, the firm is immediately liquidated. Debtholders receive the liquidation value of the total unleveraged asset value, i.e., of the unleveraged assets in place plus the unleveraged growth option, less bankruptcy costs. The proceeds from liquidating the firm upon default correspond to Λ_i times the total unleveraged asset value. The bankruptcy costs include, for example, lawyers' and accountants' fees, or the value of the managerial time spent in administering the bankruptcy. They correspond to a fraction $1 - \alpha_i$ of the proceeds from liquidation, with $\alpha_i \in (0, 1]$. Hence, the recovery rates to debtholders correspond to $\Lambda_i \alpha_i$ times the unleveraged asset value upon default. The assumption that debtholders also recover a fraction of the unleveraged expansion option implies that the option is transferrable. Upon default, however, the expansion opportunities are far out-of-the-money and have, consequently, only limited value. Hence, assumptions concerning their transferability or recovery rates have a negligible impact on our results.

Equityholders face the following decisions. First, once debt has been issued, they select the default, expansion, and investment financing policies that maximize the equity value. Second, they determine the initially optimal capital structure by choosing a coupon that maximizes the firm value. We do not incorporate debt restructuring neither when the option is exercised nor at endogenous restructuring points.

4.4 Model solution

Firms can finance investments by selling assets or by issuing equity in each regime, which leaves us with four different financing strategies: financing by issuing equity in good states and selling assets in bad states, financing by issuing equity in both good states and bad states, financing by selling assets in good states and issuing equity in bad states, and financing by selling assets in both good and bad times. In what follows, the solution for a firm that applies the first financing strategy, i.e., financing by issuing equity in good states and selling assets in bad states, is derived in detail. The solutions for the second to fourth financing strategies can be derived analogically. We first present the values of corporate securities after investment, and for the growth option. We then solve for the values of corporate securities before investment by backward induction.

4.4.1 Value of corporate securities after investment

After exercising the expansion option, a firm consists of only invested assets, endowed with the initially determined optimal coupon level. Let $\hat{d}_i(X)$ denote the value of corporate debt, $\hat{t}_i(X)$ the value of the tax shield, and $\hat{b}_i(X)$ the value of bankruptcy costs of a firm with only invested assets. The standard solutions for the values of these securities are derived in 1.2. The firm value after investment, $\hat{v}_i(X)$, can be expressed as the value of assets in place plus the tax shield minus bankruptcy costs:

$$\hat{v}_i(X) = (1-\tau)y_i X + \hat{t}_i(X) - \hat{b}_i(X). \tag{4.4.1}$$

The total firm value equals the sum of debt and equity values. Hence, the equity value after investment, $\hat{e}_i(X)$, can be written as

$$\hat{e}_i(X) = \hat{v}_i(X) - \hat{d}_i(X). \tag{4.4.2}$$

The default policy is chosen by equityholders to maximize the ex post value of equity. As the equity value at the time of default corresponds to zero, this policy can be calculated by equating the first derivative of the equity value to zero at the default boundary in each regime:

$$\begin{cases} \hat{e}'_G(D^*_G) & = & 0 \\ \hat{e}'_B(D^*_B) & = & 0 \end{cases} \tag{4.4.3}$$

We solve this system numerically. The value of corporate securities is solved similarly for a firm with a scaled level of earnings after investment. The default policy is then expressed as a scaled earnings levels.

4.4.2 The value of the growth option

To study cyclicality of expansion options, we extend the model of Arnold et al. (2013) by allowing regime-dependency of the additional earnings factor s_i, and the exercise cost K_i of the option. For each regime i, a growth option is exercised immediately whenever $X \geq X_i$ (option exercise region); otherwise, it is optimal to wait (option continuation region). This structure results in a system of ordinary differential equations (ODEs) with associated boundary conditions given in 1.3. The following proposition presents the value of the growth option, $G_i(X)$, in a leveraged firm (leveraged growth option) that finances the exercise cost by issuing equity in good states, and by selling assets in bad states for $X_G \leq X_B$.

Proposition 1. For any given pair of exercise boundaries $[X_G, X_B]$, the value of the leveraged growth option in regime i is given by

$$G_i(X) = \left\{ \begin{array}{lll} \bar{A}_{i3}X^{\gamma_3} + \bar{A}_{i4}X^{\gamma_4} & 0 \leq X < X_G, & i = G, B \\ \bar{C}_1 X^{\beta_1^B} + \bar{C}_2 X^{\beta_2^B} + \bar{C}_3 X + \bar{C}_4 & X_G \leq X < X_B, & i = B \\ (1-\tau)s_B X y_B - K_B/\Lambda_B & X \geq X_B & i = B \\ (1-\tau)s_G X y_G - K_G(1+\Upsilon_G) & X \geq X_G & i = G \end{array} \right\}, \tag{4.4.4}$$

where

$$\begin{aligned} \beta_{1,2}^B &= \frac{1}{2} - \frac{\tilde{\mu}_B}{\tilde{\sigma}_B^2} \pm \sqrt{\left(\frac{1}{2} - \frac{\tilde{\mu}_B}{\tilde{\sigma}_B^2}\right)^2 + \frac{2(r_B + \tilde{\lambda}_B)}{\tilde{\sigma}_R^2}}, \\ \bar{C}_3 &= \tilde{\lambda}_B \frac{(1-\tau)s_G y_G}{r_B - \tilde{\mu}_B + \tilde{\lambda}_B}, \\ \bar{C}_4 &= -\tilde{\lambda}_B \frac{K_B/\Lambda_B}{r_B + \tilde{\lambda}_B}. \end{aligned} \tag{4.4.5}$$

The parameters γ_3 and γ_4 correspond to the positive roots of the quadratic equation

$$(\tilde{\mu}_B\gamma + \frac{1}{2}\tilde{\sigma}_B^2\gamma(\gamma-1) - \tilde{\lambda}_B - r_B)(\tilde{\mu}_G\gamma + \frac{1}{2}\tilde{\sigma}_G^2\gamma(\gamma-1) - \tilde{\lambda}_G - r_G) = \tilde{\lambda}_B\tilde{\lambda}_G. \tag{4.4.6}$$

$\bar{A}_{Gk}$ is a multiple of $\bar{A}_{Bk}$, $k = 3, 4$, with the factor $\bar{l}_k := \frac{1}{\tilde{\lambda}_G}(r_G + \tilde{\lambda}_G - \tilde{\mu}_G\gamma_k - \frac{1}{2}\tilde{\sigma}_G^2\gamma_k(\gamma_k - 1))$, i.e., $\bar{A}_{Bk} = \bar{l}_k\bar{A}_{Gk}$, and r_i^p is the perpetual risk-free rate given by

$$r_i^p = r_i + \frac{r_j - r_i}{\tilde{p} + r_j}\tilde{p}\tilde{f}_j, \tag{4.4.7}$$

in which $\tilde{p} = \tilde{\lambda}_1 + \tilde{\lambda}_2$ is the risk-neutral rate of news arrival and $\left(\tilde{f}_G, \tilde{f}_B\right) = \left(\frac{\lambda_B}{\tilde{p}}, \frac{\lambda_G}{\tilde{p}}\right)$ is the long-run risk-neutral distribution. $\left[\bar{A}_{G3}, \bar{A}_{G4}, \bar{C}_1, \bar{C}_2\right]$ solve a linear system given in Section 1.3.

Proposition 1 determines the value of the growth option for any given pair of exercise boundaries $X_G \leq X_B$. The optimal exercise boundaries of the leveraged growth option will be determined in the next section, as they depend on the capital structure of the firm holding the option. Additionally, note that the value of the growth option also depends on both the asset liquidity and the equity issuance cost.

For the derivation of the values of corporate securities before investment, we also need the value of an unleveraged option G_i^{unlev} that corresponds to the value of an option in an all equity financed firm. This value does not depend on the capital structure of a firm. Hence, the optimal exercise boundaries simply maximize the value of the option. They can, therefore, be directly derived by additionally imposing smooth-pasting conditions at the corresponding option exercise boundaries as shown in 1.3.

As we consider a regime-dependent additional earnings factor s_i and exercise cost K_i of the option, we also encounter the case in which the exercise boundary in good states, X_G, is larger than the exercise boundary in bad states, X_B. It occurs when s_B is considerably larger than s_G, or when K_B is much smaller than K_G. The solution of this case can be obtained immediately by interchanging the regime names in the derivation of the presented solution with $X_G \leq X_B$.

4.4.3 Value of corporate securities before investment

Once the values of corporate securities after investment and of the growth option are known, we can determine the values of corporate securities before investment of a firm that finances the exercise cost by issuing equity in good times, and by selling assets in bad times. Let $d_i(X)$ denote the debt value of a firm with invested assets and an expansion option in regime $i = G, B$, and G_i^{unlev} the value of an unleveraged option derived in the 1.3. Proposition 2 states the value of debt before investment.

Proposition 2. For any given set of default and exercise boundaries $[D_G, D_B, X_G, X_B]$, the value of infinite maturity debt in regime i is given by

$$d_i(X) = \begin{cases} \alpha_i \Lambda_i \left((1-\tau) X y_i + G_i^{unlev}(X)\right) & X \leq D_i, \quad i = G, B, \\ C_1 X^{\beta_1^G} + C_2 X^{\beta_2^G} + C_5 X^{\gamma_3} + C_6 X^{\gamma_4} & \\ \quad + \tilde{\lambda}_G \frac{\alpha_B \Lambda_B y_B (1-\tau)}{r_G - \tilde{\mu}_G + \tilde{\lambda}_G} X + \frac{c}{r_G + \tilde{\lambda}_G} & D_G < X \leq D_B, \quad i = G \\ A_{i1} X^{\gamma_1} + A_{i2} X^{\gamma_2} + A_{i3} X^{\gamma_3} + A_{i4} X^{\gamma_4} + \frac{c}{r_i^P} & D_B < X \leq X_G, \quad i = G, B \\ B_1 X^{\beta_1^B} + B_2 X^{\beta_2^B} + Z(X) + \tilde{\lambda}_B \frac{c}{r_i^P (r_B + \tilde{\lambda}_B)} + \frac{c}{r_B + \tilde{\lambda}_B} & X_G < X \leq X_B, \quad i = B \\ \hat{d}_G((s_G+1)X) & X > X_G, \quad i = G \\ \hat{d}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau) X_{\bar{t}} y_B}) X\right) & X > X_B, \quad i = B, \end{cases} \tag{4.4.8}$$

where

$$\beta_{1,2}^i = \frac{1}{2} - \frac{\tilde{\mu}_i}{\tilde{\sigma}_i^2} \pm \sqrt{\left(\frac{1}{2} - \frac{\tilde{\mu}_i}{\tilde{\sigma}_i^2}\right)^2 + \frac{2(r_i + \tilde{\lambda}_i)}{\tilde{\sigma}_i^2}} \tag{4.4.9}$$

$$C_5 = \alpha_B \Lambda_B \frac{\bar{l}_3}{l_3} \bar{A}_{G3}^{unlev}, \tag{4.4.10}$$

$$C_6 = \alpha_B \Lambda_B \frac{\bar{l}_4}{l_4} \bar{A}_{G4}^{unlev}, \tag{4.4.11}$$

and

$$Z(X) = \tilde{\lambda}_B B_5 X^{\gamma_1} + \tilde{\lambda}_B B_6 X^{\gamma_2}. \tag{4.4.12}$$

The parameters B_5 and B_6 are given by

$$B_5 = \frac{(s_B+1)^{\gamma_1} \hat{A}_{G1}}{r_B - \tilde{\mu}_B \gamma_1 - \frac{1}{2} \tilde{\sigma}_B^2 \gamma_1 (\gamma_1 - 1) + \tilde{\lambda}_B} \tag{4.4.13}$$

and

$$B_6 = \frac{(s_B+1)^{\gamma_2} \hat{A}_{G2}}{r_B - \tilde{\mu}_B \gamma_2 - \frac{1}{2} \tilde{\sigma}_B^2 \gamma_2 (\gamma_2 - 1) + \tilde{\lambda}_B}, \tag{4.4.14}$$

and $\gamma_k, k = 1, 2, 3, 4$ are the roots of the quadratic equation

$$\left(\tilde{\mu}_B\gamma + \frac{1}{2}\tilde{\sigma}_B^2\gamma(\gamma-1) - \tilde{\lambda}_B - r_B\right)\left(\tilde{\mu}_G\gamma + \frac{1}{2}\tilde{\sigma}_G^2\gamma(\gamma-1) - \tilde{\lambda}_G - r_G\right) = \tilde{\lambda}_B\tilde{\lambda}_G. \quad (4.4.15)$$

A_{Bk}, $k = 1, 2, 3, 4$, is a multiple of A_{Gk} with the factor

$$l_k := \frac{1}{\tilde{\lambda}_G}(r_G + \tilde{\lambda}_G - \tilde{\mu}_G\gamma_k - \frac{1}{2}\tilde{\sigma}_G^2\gamma_k(\gamma_k - 1)), \quad (4.4.16)$$

and r_i^p denotes the perpetual risk-free rate given by

$$r_i^p = r_i + \frac{r_j - r_i}{\tilde{p} + r_j}\tilde{p}\tilde{f}_j, \quad (4.4.17)$$

in which $\tilde{p} = \tilde{\lambda}_1 + \tilde{\lambda}_2$ is the risk-neutral rate of news arrival and $\left(\tilde{f}_G, \tilde{f}_B\right) = \left(\frac{\lambda_B}{\tilde{p}}, \frac{\lambda_G}{\tilde{p}}\right)$ is the long-run risk-neutral distribution. $\hat{d}_i\left(\cdot\right)$ denotes the value of debt of a firm with only invested assets.
$[A_{G1}, A_{G2}, A_{G3}, A_{G4}, C_1, C_2, B_1, B_2]$ solve a linear system given in Section 1.4.

Proof. See 1.4. □

Proposition 2 shows that the firm faces three different regions depending on the value of X. Below the default threshold, i.e., $X \leq D_i$, the firm is in the default region in which it defaults immediately. Debtholders receive a fraction $\alpha_i\Lambda_i$ of the total after tax asset value.

The firm is in the continuation region if X is between the default threshold and the exercise boundary, i.e., if $D_i < X \leq X_i$. In this region, debt value is determined by three components. The first component is the value of a risk-free claim to the perpetual stream of coupon. The second and third components reflect the changes in the value of debt that occur either due to the idiosyncratic shock reaching a boundary or due to a regime switch. For the region $D_B < X \leq X_G$, i.e., when the firm is in the continuation region in both good states and bad states, the solution consists of five terms. The value of the risk-free claim to the coupon is given by the last term. The coupon needs to be discounted by the perpetual risk-free rate r_i^p that incorporates the expected future time spent in each regime. The first four terms capture the changes in value due to the idiosyncratic shock X hitting a region boundary or due to a change of regime. When $D_G < X \leq D_B$, i.e., the firm is in the continuation region only in good states, the solution consists of six terms. The last term is the value of the risk-free claim to the coupon, in which the discount rate is given by the interest rate in good states, r_G, increased by $\tilde{\lambda}_G$ to reflect the possibility of a regime switch to the bad state. The first five terms capture the changes in debt value that occur when the idiosyncratic shock reaches a boundary or when the regime switches to the bad state triggering immediate default. For the region $X_G < X \leq X_B$, i.e., when the firm is in the continuation region only in bad states, the solution consists of five terms. The last term is the value of a risk-free perpetual claim to the coupon. To account for a possible regime switch to the good state, the discount rate is given by the interest rate in the bad state, r_B, increased by $\tilde{\lambda}_B$. The remaining four terms capture the value changes due to reaching a region boundary, either X_G from above or X_B from below, or due to a regime switch to a good state triggering immediate option exercise financed with equity.

Finally, the debt value in the exercise region, reached when $X > X_i$, incorporates the financing source for the option exercise cost. In the good states, the option exercise cost K_G is financed by issuing new equity of $K_G(1 + \Upsilon_G)$. Hence, the earnings of the firm are scaled by $s_G + 1$. In the bad states, the exercise cost K_B is financed by selling $\frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B}$ of the assets in place, such that the earnings of the firm are scaled by $(s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B})$.

The value of the tax shield before investment can be calculated by using the solution (4.4.8) in Proposition 2, in which c and α are replaced by $c\tau$ and zero, respectively, and $\hat{d}_i$ in the last line line of (4.4.8) is replaced by $\hat{t}_i$. The value of bankruptcy costs before investment is derived by using the same steps as for debt value with two simple modifications. First, c and α need to be replaced by zero and $(1 - \alpha)$, respectively. Second, while the going concern value of the expansion option is given by its leveraged value, the value of the option at default corresponds to its unleveraged value. Therefore, the expansion option's value switches from $G_i(X)$ to $\alpha_i \Lambda_i G_i^{unlev}(X)$ upon default. As a consequence, the functional form of the solution (4.4.8) in the default region $X \leq D_i$ needs to be adapted to $(1 - \alpha_i \Lambda_i) y_i X(1 - \tau) - \alpha_i \Lambda_i G_i^{unlev}(X) + G_i(X)$. The 1.5 shows the resulting solution for the value of bankruptcy costs $b_i(X)$.

Next, the total firm value before investment, f_i, in regime $i = G, B$ is given by the value of assets in place $(1-\tau)y_i X$, plus the value of the expansion option $G_i(X)$ and the value of tax benefits from debt $t_i(X)$, minus the value of default costs $b_i(X)$, i.e.,

$$f_i(X) = (1-\tau)y_i X + G_i(X) + t_i(X) - b_i(X). \tag{4.4.18}$$

As the total firm value equals the sum of debt and equity values, the equity values before investment of a firm that finances investment by issuing equity in a good state and selling assets in a bad state, $e_i^{ES}(X,c)$, $i = G, B$, can be written as

$$e_i(X,c) = f_i(X) - d_i(X) = (1-\tau)y_i X + G_i(X) + t_i(X) - b_i(X) - d_i(X). \tag{4.4.19}$$

Equity-holders select the default and investment policies that maximize the ex post value of equity. Denote these policies by D_i^* and X_i^*, respectively. The default policy that maximizes the equity value is determined by setting the first derivative of the equity values to zero at the default boundary in each regime. Simultaneously, optimality of the option exercise thresholds is achieved by equating the first derivative of the equity values at the exercise thresholds to the first derivative of the equity values of a firm with only invested assets after expansion, evaluated at the corresponding earnings in both regimes. These four optimality conditions represent smooth-pasting conditions for equity of a firm that finances the option exercise cost by issuing equity in good states and selling assets in bad states at the respective boundaries:

$$\begin{cases} e'_G(D_G^*, c) &= 0 \\ e'_B(D_B^*, c) &= 0 \\ e'_G(X_G^*, c) &= \hat{e}'_G\left((s_G+1)X_G^*, c\right) \\ e'_B(X_B^*, c) &= \hat{e}'_B\left(((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B})X_B^*), c\right). \end{cases} \tag{4.4.20}$$

The system is solved numerically. As the equations in system Eqs. (4.4.20) are evaluated simultaneously, the four conditions are interdependent. Similar systems can be derived for a firm that finances the option exercise cost by issuing equity in both good states and bad states, by selling assets in good states and issuing equity in bad states, or by selling assets in both good states and bad states.

Denote by $e_i^{m,n*}(X, c)$ the equity value given optimal ex post default and expansion thresholds. The exponents $m \in [E, S]$ and $n \in [E, S]$ indicate the financing strategy in good states and bad states, respectively. E denotes equity financing and S selling assets. For each coupon level c, equityholders select the ex post financing strategy Ω_i^* that maximizes the value of equity, i.e.,

$$\Omega_i^* := \text{argmax}_{m,n} \left(e_i^{m,n*}(X, c) \right). \tag{4.4.21}$$

Debtholders anticipate the ex post optimal default and expansion policies, as well as the optimal financing strategy of shareholders. As debt-issue proceeds accrue to shareholders, they do not only care about the value of equity, but also about the initial valuation of debt. Hence, the optimal capital structure is determined ex ante by the coupon level c^* that maximizes the value of equity and debt, i.e., the value of the firm. Denote by $f_i^*(X)$ the firm value given optimal default boundaries, expansion thresholds, and the optimal financing strategy. The ex ante optimal coupon of the firm solves

$$c_i^* := \text{argmax}_c f_i^*(X). \tag{4.4.22}$$

To summarize, equityholders face the following decisions: First, they choose the default and expansion thresholds that maximize the ex post value of equity for each coupon and financing strategy. Second, equityholders select the financing strategy that maximizes the ex post value of equity for each coupon. Finally, they determine the initial capital structure that maximizes the ex ante value of equity.

4.5 Results

In this section, we study the implications of the model for a typical model firm. We start by describing parameter choices for our baseline calibration before we derive the hypothesis in Section 4.5.2.

4.5.1 Parameter choice

We summarize our parameter choices in Table 4.2. Panel A shows the firm characteristics. The initial value of the idiosyncratic earnings X is set to 10. While the starting value for earnings is arbitrary, our results do not depend on this choice. We set the tax advantage of debt to $\tau = 0.15$ as suggested in the literature (e.g., Hackbarth et al. 2006). Bhamra et al. (2010b) estimate growth rates and systematic volatilities of earnings in a two-regime model. Their estimates are similar to those obtained by other authors who jointly estimate consumption and dividends with a state-dependent drift and volatility (e.g., Bonomo and Garcia 1996). Hence, we set earnings growth rates (μ_i) and volatilities ($\sigma_i^{X,C}$) to their empirical counterparts reported in Bhamra et al. (2010b). The idiosyncratic volatility is set to 0.168. Arnold et al. (2013) show that using this volatility calibration, a simulated sample of firms with growth options has an average asset volatility of approximately 25%, which corresponds to the average asset volatility of firms with rated debt outstanding (see Schaefer and Strebulaev 2008).

The main costs of external equity discussed by Fazzari et al. (1988) are tax costs, adverse selection premia, and flotation costs. Hansen (2001) and Corwin (2003) estimate equity issuance costs around 7% for IPOs and SEOs, respectively. Altinkilic and Hansen (2000) argue that equity costs derive mainly from the variable component. The linear variable component estimated in Hennessy and Whited (2007) is 9.1%. Concerning cyclicality, Bayless and Caplinsky (1996) find that a typical hot market issuer would forego up to 2.33% in additional equity value if he would issue in a cold market instead. To reflect these empirical quantities, we choose as a benchmark case $\Upsilon_G = 0.08$ and $\Upsilon_B = 0.1$. This setting gives us a cyclicality for the equity issuance cost of a two percentage points difference between good and bad states, and an average total equity issuance cost of 8.71%.[12] In the comparative statics we vary the equity issuance cost to analyze how they affect the decision of firms to sell assets to finance the investment cost.

There are only a few empirical studies that estimate the cost of selling assets. Pulvino (1998) finds costs of selling commercial aircrafts between zero and 14%. Strebulaev

[12]The weights for this average correspond to the long-run distribution of the Markov chain. One could also simulate a large sample of firms and determine the weights according to the occurrence of equity issues in the two states.

Table 4.2: **Baseline parameter choice**
This table summarizes our baseline parameter choice. Panel A lists the annualized parameters of a typical Compustat firm. Panels B and C report our parameter choice for the expansion option and the macroeconomy, respectively.

Parameter	Parameter value	
Panel A: Firm Characteristics	*Good State (G)*	*Bad State (B)*
Initial earnings level (X)	10	10
Tax advantage of debt (τ)	0.15	0.15
Earnings growth rate (μ_i)	0.0782	-0.0401
Systematic earnings volatility ($\sigma_i^{X,C}$)	0.0834	0.1334
Equity issuance costs (Υ_i)	0.08	0.1
Asset Liquidity (Λ_1)	0.9259	0.9091
Recovery rate (α_i)	0.63	0.57
Panel B: Expansion Option Parameters of a Typical Firm		
Exercise price (K_i)	298	260
Scale parameters (s_i)	1.0925	1.03
Panel C: Economy		
Rate of leaving regime i (λ_i)	0.2718	0.4928
Consumption growth rate (θ_i)	0.0420	0.0141
Consumption growth volatility (σ_i^C)	0.0094	0.0114
Rate of time preference (ρ)	0.015	0.015
Relative risk aversion (γ)	10	10
Elasticity of intertemporal substitution (Ψ)	1.5	1.5

(2007) assumes that the cost of selling assets lies between 0.05 to 0.25%. Acharya et al. (2007) show that creditors of defaulted firms recover 10 to 15 percentage points less in a distressed state of the industry than in a healthy state of the industry, i.e., that asset liquidity is cyclical. Overall, we only have vague empirical evidence on the appropriate choice of the parameters for the cost of selling assets. Hence, to avoid that our results are driven by this choice when analyzing firms' endogenous financing decisions, we set $\Lambda_{\bar{i}}$ such that $K_{\bar{i}}/\Lambda_{\bar{i}} = K_{\bar{i}}(1+\Upsilon_{\bar{i}})$, i.e., the friction adjusted cost of exercising the expansion option by selling assets corresponds to the one of exercising the expansion option by issuing new equity. This calibration yields $\Lambda_G = 0.9259$ and $\Lambda_B = 0.9091$.

One caveat of the presented analysis is that the equity issuance cost and asset liquidity are hard to estimate. We address this issue in two different ways. First, we base our parameter choice on empirical results of previous works. Second, we perform numerous robustness checks with alternative equity issuance cost and asset liquidity parameters. The tests show that our qualitative predictions are not affected by varying these parameters within plausible ranges.

Bankruptcy costs are assumed to be 30% of the unleveraged assets' liquidation proceeds. Recovery rates are $\Lambda_i(1-0.3)$, so they are 0.63 in good states and 0.57 in bad states. These values are in accordance with the unconditional standard of 0.6 used in the literature (e.g. Hackbarth et al. 2006, Chen 2010), and with the notion in Acharya et al. (2007) that recovery rates fall during bad states.

Panel B of Table 4.2 shows the parameters we use to capture growth options. We select exercise prices of $K_G = 298$ and $K_B = 260$, respectively. The ratio K_G/K_B corresponds to the ratio of the value of a given level of earnings in good states to the value of the same earnings in bad states. In other words, the exercise price changes by the same factor as the price of assets in place when the regime switches. We validate the robustness of our predictions by presenting the results for alternative choices of the absolute level of K_i.

The scale parameter s_i depends on the cyclicality of the firm's option. We use baseline scale parameters of $s_G = 1.0925$ and $s_B = 1.03$. These parameters imply that, given optimal financing at initiation, the average q is 1.3. The q of a model firm is obtained by dividing the value of the firm by the value of its invested assets. To calculate the average q, the initial q in good and bad states is weighted by the long-run distribution of the Markov chain. To generate typical firms with different degrees of the cyclicality of the expansion option, we alter s_G and s_B while keeping the size of the average q at initiation fixed at its empirical counterpart.

Finally, Panel C, lists the variables describing the underlying economy. The rates of leaving regime i (λ_i), the consumption growth rates (θ_i), and the consumption growth volatilities σ_i^C are estimated in Bhamra et al. (2010b). In the model economy, the expected duration of regime B (R) is 3.68 (2.03) years, and the average fraction of time spent in regime B (R) is 64% (36%).

The annualized rate of time preference, ρ, is 0.015; the relative risk aversion, γ, is equal to 10; and the elasticity of intertemporal substitution, Ψ, is set to 1.5. This parameter choice is commonly used in the literature (e.g., Bansal and Yaron 2004, Chen 2010). It implies that the nominal interest rates are $r_G = 0.0736$ and $r_B = 0.0546$. The relative decline in the value of invested assets following a shift from good to bad states is equal to 12.61%, which is similar to the one assumed in, e.g., Hackbarth et al. (2006).

4.5.2 Derivation of the model predictions

Exercising an expansion option has two implications for a firm that finances the exercise cost of the option by issuing equity. First, it increases total earnings. Second, the total asset volatility decreases because the expansion option is riskier than the assets in place (see e.g. Arnold et al. 2013). Both effects induce a wealth transfer from equityholders to debtholders as debt becomes less risky. This wealth transfer problem is more severe for firms with larger leverage. The reason is that if leverage increases, debt becomes riskier and, consequently, more sensitive to earnings and asset volatility changes.

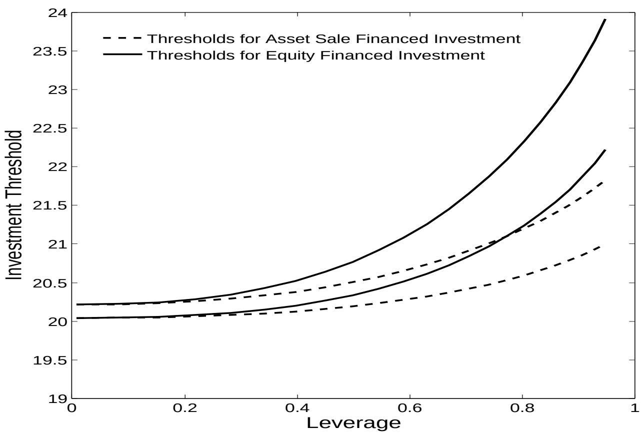
The cost of exercising the expansion option by selling assets can be larger than the ones of exercising the expansion option by issuing new equity, i.e., $K_{\bar{i}}/\Lambda_{\bar{i}}$ may be larger than $K_{\bar{i}}(1 + \Upsilon_{\bar{i}})$. At the same time, however, selling assets upon investment increases leverage which renders debt more risky. The corresponding wealth transfer from debtholders to equityholders ameliorates the initial wealth transfer problem from the exercise of the expansion option. Hence, equityholders trade off the incremental friction cost of selling assets over the equity issuance cost against the reduction in the wealth transfer when deciding whether to sell assets or to issue equity to finance the exercise of the expansion option. As the wealth transfer problem is more severe for firms with larger leverage, equityholders of such firms have a particularly pronounced tendency to finance the expansion option by selling assets. This insight leads to our first model prediction.

Prediction 1. Equityholders of firms with a larger leverage have a higher tendency to finance the exercise cost of the expansion option by selling assets.

Prediction 1 explains why we find that, empirically, the correlation between asset sales and investment is higher for firms with larger leverage.

The wealth transfer problem has an impact on equityholders' investment timing. The equity value maximizing earnings thresholds for the option exercise of a firm that finances the investment cost by issuing equity are plotted in Figure 4.1. The lower solid line depicts the optimal investment threshold for various levels of leverage in the good state. The higher solid line is the corresponding threshold in the bad state. As expected, the firm invests earlier in the good state. We refer to the investment thresholds without debt (at zero leverage) as the option value-maximizing threshold. The larger the leverage, the later the equityholders invest compared to the option value-maximizing threshold due to the wealth transfer problem (underinvestment). The dashed lines in Figure 4.1 depict the optimal investment thresholds of a firm that sells assets to finance the exercise cost of the option. The lower dashed line is the threshold in the good state, the higher dashed line the one in bad times.

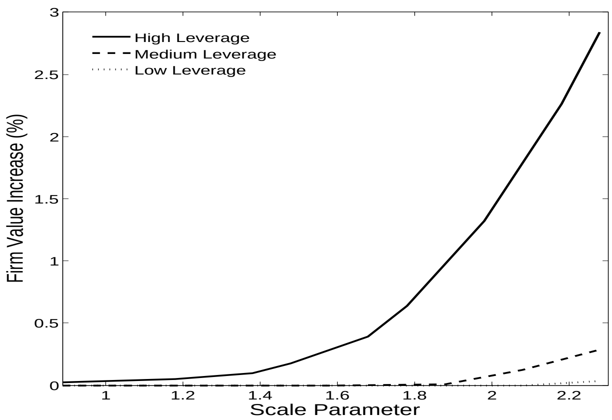
Figure 4.1: **Optimal Investment Thresholds.** This figure shows the earnings levels at which equityholders optimally exercise the growth option for a range of corporate leverage ratios. The lower and upper solid lines are the optimal investment thresholds for a firm that finances the exercise costs of the option by issuing equity in good states and bad states, respectively. The lower and upper dashed lines are the corresponding investment thresholds for a firm that finances the exercise costs of the option by selling assets.



For the baseline specification and most alternative parameter combinations, financing asset sales mitigate the underinvestment problem compared to equity financed investment. The option exercise thresholds for financing asset sales in Figure 4.1 are closer to the option value-maximizing threshold, particularly for large leverage firms in which the wealth transfer problem is more pronounced.[13]

Figure 4.2 illustrates the quantitative effect of allowing equityholders into financing asset sales on the value of a firm.

Figure 4.2: **Financing Asset Sales and Firm Value.** This figure illustrates the impact of financing asset sales on the value of firms. The solid line shows the relationship between the increase in the value of a firm from admitting financing asset sales and the scale parameter s_G for high leverage firms. The parameter s_B is obtained by deducing 0.0625 from s_G. High leverage firms have an initial leverage ratio of 0.75. Leverage is defined as debt value divided by the value of the firm. The dashed and dotted lines plot the relationship for medium leverage firms with an initial leverage of 0.5 and for low leverage firms with an initial leverage of 0.35, respectively.



The solid line shows the relationship between the increase in the value of a firm from permitting financing asset sales and the scale parameter s_G for high leverage firms. The parameter s_B is obtained by deducing 0.0625 from s_G. High leverage firms have an initial leverage ratio of 0.75. The remaining parameters are set according to the baseline firm.

[13]For certain parameter combinations with a high scale parameter s_i, and a low exercise cost K_i, financing asset sales can also induce overinvestment such that the dashed thresholds in Figure 4.1 decrease with leverage. The reason is that the expansion option is almost immediately exercised for these parameter combinations. As a consequence, the investment cost constitutes a much larger fraction of the asset value upon exercise than for parameter combinations for which the option is exercised at a larger level of X. Hence, the impact on leverage from financing asset sales is also larger, and the corresponding higher wealth transfer can induce equityholders to exercise the option at an earnings level below the option value-maximizing threshold.

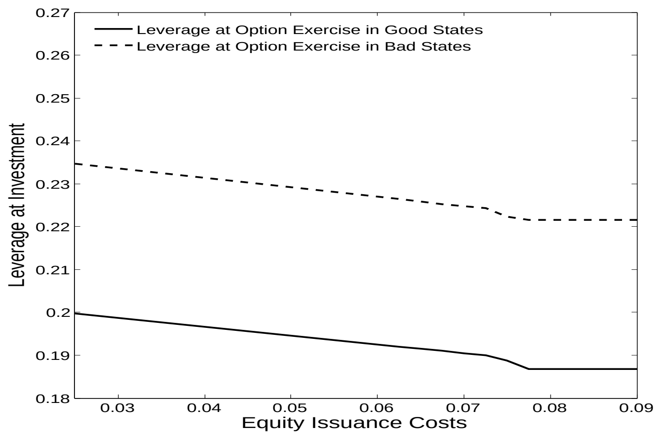
In particular, the friction cost of selling assets corresponds to the one of issuing new equity. Hence, we measure the pure impact of permitting financing asset sales on firm value from a mitigation of the underinvestment problem. The dashed and dotted lines plot the relationship for medium leverage firms with an initial leverage of 0.5 and for low leverage firms with an initial leverage of 0.35, respectively. The value of all firms increases with financing asset sales because their allowance induces equityholders to follow an option exercise policy that is closer to the First Best than in the case in which financing asset sales are prohibited. This finding explains why it is optimal for equityholders to negotiate conventions in asset sale covenants that still allow the firm to use financing asset sales as described in the literature (e.g., Smith and Warner 1979, Bradley and Roberts 2004, Nini et al. 2009). The larger the scale parameter and the higher the leverage in Figure 4.2, the stronger the positive impact of permitting financing asset sales on the value of a firm. The reason is that the mitigation of the underinvestment problem from financing asset sales is particularly valuable if the value of the growth option is high, and the wealth transfer problem is large due to high leverage.

We now investigate how the wealth transfer problem of the baseline firm depends on different states of the business cycle. During bad times, leverage increases because the assets of a firm lose more value relative to the decrease in value of the outstanding debt. At the same time, Figure 4.1 shows that equityholders optimally invest at a higher level of earnings than in the bad state. A higher investment threshold induces a larger asset value upon investment, and, hence, a lower leverage. To see which effect dominates, Figure 4.3 plots leverage upon investment for a baseline firm with an initially optimal capital structure and endogenous choice of the financing strategy for a range of equity issuance cost parameters. The equity issuance cost parameter in good states, Υ_G, is plotted on the x-axis. The corresponding equity issuance cost parameter in bad states is determined by adding 0.02. In this way, we maintain the same difference between the equity issuance costs in good states and bad states as in the baseline parameter specification. The figure shows that leverage at the optimal investment threshold during bad states (dashed line) is always higher than during good states (solid line). Because the wealth transfer problem is more severe for higher leverage, and because asset sales ameliorate this problem, equityholders' trade off the cost of financial frictions against the debt overhang cost, which leads to the second model prediction.

Prediction 2. Firms are more likely to fund investments by selling assets during bad business cycle states.

Prediction 2 provides an explanation for why the correlation between asset sales and investment is significantly higher during bad business cycle states in our Compustat sample.

Figure 4.3: **Leverage at Investment.** This figure shows the leverage ratios upon investment of a firm that optimally finances the exercise costs of the option in good states (solid line) and bad states (dashed line).



The procyclical nature of aggregate investment (see e.g. Barro 1990) suggests that growth options are generally more valuable during good times than during bad times. We argue that the degree of this cyclicality of the growth option is different across firms. To model a firm with a relatively higher value of the expansion option in the good states, i.e., with a higher cyclicality of the expansion option, relative to the baseline firm, we increase the scale parameter in good times, s_G, from 1.0925 to 1.099, and decrease the scale parameter in bad states, s_B, from 1.03 to 1.005, leaving the average q at initiation unchanged at 1.3.[14] A higher scale parameter in good times, and a lower scale parameter

[14]The cyclicality of the expansion option can also be altered by changing the investment cost K_i. The qualitative predictions from our model also hold in this case.

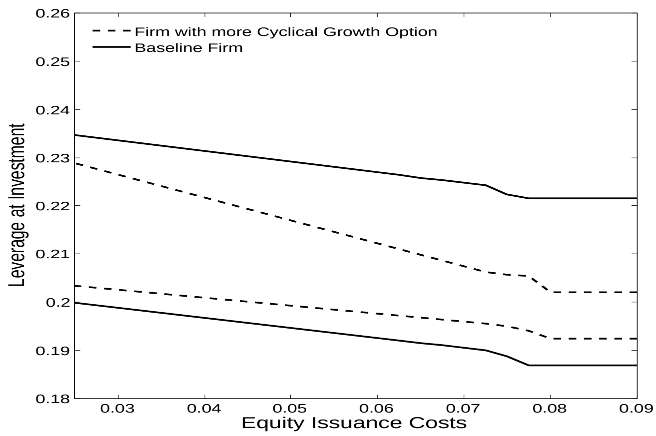
in bad times induce that it is relatively more attractive to exercise the option in the good state, and relatively less attractive to exercise in the bad state compared to the baseline firm. The optimal investment threshold in the good state decreases from 20.18 to 19.67, and the one in the bad state increases from 20.48 to 22.23. Hence, firms with a relatively higher value of the expansion option in good times have a lower probability to invest during bad times. Additionally, Figure 4.4 compares leverage levels upon investment of the baseline firm to the ones of the firm with a more valuable growth option in a good state. The lower and higher solid lines depict leverages upon investment for a range of equity issuance parameters for the baseline firm in good times and bad states, respectively. The lower and higher dashed lines show leverage ratios at investment in good and bad times of the firm with a more valuable growth option in good states. Since the baseline firm optimally invests at a lower earnings threshold in bad times than the firm with a more cyclical growth option, it has a lower asset value and, hence, a higher leverage at investment during bad times. As the wealth transfer problem is more severe for firms with higher leverage, and because equityholders trade off the financial friction cost differential between equity issuance and asset sales against the reduction in the wealth transfer problem when selecting the financing source, we can phrase our third model prediction.

Prediction 3. Firms with a more valuable expansion option during bad business cycle states are more likely to finance investments by selling assets during bad business cycle states than firms with a more cyclical expansion option.

This prediction explains our empirical finding that the correlation between asset sales and investment is higher for firms with a low cyclicality of the expansion option during bad times.

Figure 4.5 summarizes the implications of the wealth transfer problem upon investment on equityholders' endogenous financing choice for the baseline firm. On the x-axis, we again plot the equity issuance cost in a good state. The y-axis shows the interest payments that determine a firm's leverage ratio. On the left hand side of the solid line, equityholders optimally select equity financing in both regimes. On the right hand side of the dashed line, firms prefer financing asset sales in both regimes. Between the two lines the firms' optimal financing strategy yields the issuance of equity in good times, and selling assets

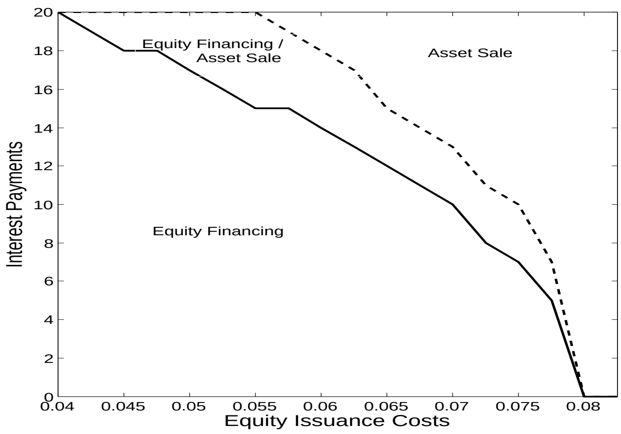
Figure 4.4: **Leverage at Investment and Cyclicality of the Growth Option.** The lower and higher solid lines are the leverage ratios upon investment of the baseline firm that optimally finances the exercise costs of the option in good states and bad states, respectively. The lower and higher dashed lines are the corresponding leverage ratios upon investment of a firm with a more cyclical growth option than the baseline firm.



in bad times. Remember that in case of the baseline firm with an equity issuance cost of 0.08 in good states and 0.1 in bad states, the cost of selling assets, Λ_i, is calibrated such that the friction cost of issuing equity corresponds to the friction cost of selling assets. In an unleveraged firm as shown on the x-axis, equityholders simply select the financing source based on this financing friction cost: If the equity issuance cost in good states is smaller than 0.08, they finance the exercise cost of the option by issuing equity; otherwise, they finance this cost by selling assets. The figure shows that for larger interest payments, the range of equity issuance costs for which equityholders prefer equity financing in both regimes declines, and the range for which they prefer selling assets increases. The reason is that asset sales reduce the wealth transfer problem in particular for high leverage firms, and equityholders trade off this reduction against the incremental friction cost of selling assets over issuing equity when selecting the financing source.

The figure also demonstrates the higher propensity of equityholders to select financing assets sales during bad business cycle states. The region in which they select financing

Figure 4.5: **Optimal Financing Choice.** This figure depicts equityholders' optimal financing choice. In the region to the right of the dashed line, they select asset sales in good states and bad states to finance the exercise costs of the option. In the region to the left of the solid line, they issue equity in good states and bad states. Between the dashed and the solid lines, equityholders issue equity in good states, and sell assets in bad states to finance the exercise costs.



asset sales in both regimes (on the right side of the dashed line) is smaller than the region in which they optimally sell assets during bad states (on the right side of the solid line).

4.6 Aggregate Dynamics of Simulated Samples

The analysis of a typical firm at initiation in Section 4.5.2 contributes to our understanding of the optimal choice between asset sales and equity issuance as sources of investment financing. In this section, we investigate the dynamic properties of a simulated model-implied economy, following the work of Bhamra et al. (2010a). The simulation approach is important for two reasons. First, the analysis of a typical firm at initiation in Section 4.5.2 does not allow us to analyze the dynamic features predicted by our model. We need to simulate the model to generate time series of investment, financing, and default observations over the business cycles. Comparing the resulting simulated data patterns to the ones observed in our Compustat sample enables us to validate our model. We can also measure how the propensity of model firms to use financing asset sales relates to firm and business cycle characteristics. This analysis helps us to confirm our explanations for the empirical regression results on the relation between investments and financing asset sales, and to derive new predictions on the impact of time-varying business cycle conditions on the dynamic time serial patterns of financing asset sales.

Second, the investment, financing, and default probabilities are nonlinear in firm characteristics. Hence, the analysis of a typical (average) firm does not explain the average behavior of a cross section of real firms. To solve this issue, it is important to measure the investment, financing, and default rates for simulated samples of firms that match the observed cross sectional distribution of real firm characteristics. The dynamic features of the average rates in these simulated matched samples can then be compared to the empirical average behavior of real firms. They are also used to derive new predictions.

4.6.1 Details on the Simulation

At the beginning of each simulation we generate an economy of model-implied firms. More specifically, we set up a grid of different firms, each featuring a unique combination of coupon, scale parameters, and equity issuance costs. Coupons range from two to the largest possible value such that no firm defaults immediately. The step size takes a value of two. Scale parameters for firms with a less cyclical growth opportunity range from 0.79 in the good state and 0.73 in the bad state, and for firms with a more cyclical growth opportunity from 0.80 in the good state and 0.71 in the bad state to the largest possible value such that the option is not exercised immediately, with a step size of 0.3. Equity issuance costs range from 0.04 to 0.09 in the good state, with a step size of 0.005. The equity issuance costs parameter in the bad state is obtained by adding 0.02 to the corresponding value in the good state. The remaining parameters are equal to those of the baseline firm.[15] The grid contains 849 different firm types. The earnings path of each firm type is then simulated forward 25 times over 10 years. Firms are exposed to the same macroeconomic shocks, but experience different idiosyncratic shocks, resulting in a model-implied economy populated by more than $20,000$ different firms. This economy has a broad range of leverage ratios, growth opportunities, and equity issuance costs.

[15] We have verified in simulations for various alternative grids (available upon request) that the results are qualitatively identical.

Next, we calculate the average leverage, Tobin's q, and equity issuance costs for each firm in our Compustat sample to match the model-implied economy to the cross sectional distribution of real firms (we define all empirical variables in 2). We consider a total of 1352 Compustat firms for which we obtain all three measures. Firms with a q value below 1.15, and above 2.15 are winsorized because our model-implied economies hardly contain firms with extremely low or high values of the growth option.[16]

To match the model-implied economy with their empirical counterpart we select for each observation in the Compustat sample the firm in the simulated economy that has the minimal Euclidean distance with respect to leverage, q, and the equity issuance costs. The matching is accurate, with an average Euclidean distance of 0.0226. The procedure allows us to construct a cross sectional distribution of model-implied matched firms that closely reflects its empirical counterpart. The matched firms are quarterly simulated forward over 60 years under the historical probability measure. The equityholders of each firm behave optimally conditional on current earnings and on the current business cycle: If current earnings are below the corresponding regime-dependent default boundary, they default immediately; if current earnings are above the corresponding regime-depending option exercise threshold, they exercise the expansion option and select the optimal financing source for the option exercise costs; otherwise, equityholders take no action. To maintain a balanced sample of firms when we simulate the matched firms over time, we exogenously introduce new firms. In particular, we replace each defaulted or exercised firm by a new firm whose growth option is still intact. Replaced firms have the same initial parameter values as the corresponding defaulted or exercised firm at initiation. To ensure robustness of our results, the entire simulation is repeated 100 times. We record and analyze the simulated matched samples.

4.6.2 Results for the Simulated Matched Samples

In this section, we first show that a typical simulated matched sample exhibits realistic properties to validate our model approach. We then provide additional support for the ability of our model to explain the empirical patterns that we observe in the Compustat

[16]Firms with a growth option that accounts for less than 13% of the total firm value almost never exercise their option, and firms with a growth option that accounts for more than 54% of the total firm value almost immediately exercise their option.

data, and discuss novel predictions for financing asset sales.

Table 4.3 reports the average over all simulations of the mean values, as well as the standard deviations of these means for important variables of the simulated matched samples. Besides the results for the full sample period, we also provide statistics that condition on the bad and good states, respectively.

Table 4.3: **Simulated Sample Results**
The table provides summary statistics for the simulated matched samples over the full sample period, bad states, and good states. The sample period is 50 years with simulated quarterly observations. Each simulated sample consists of 1352 firms that are matched to our Compustat sample. Firms are replaced in case of investment or default. We report the mean of the mean values of 100 simulated samples, and the standard deviation (Std) of the mean across simulations. $Total\ Assets$ (TA) is the total value of firm assets. $Investment$, $Asset\ Sale$ and $EquityFinance$ are dummy variables that are 1 if firms invest, sell assets, or issue equity, respectively. $Leverage$ is the firm's leverage. $Leverage$ and $Equity\ Value$ are scaled by total assets. The q of model firms is obtained by dividing the value of the firm by the value of its invested assets. The variable $Cov.\ Ratio$ is computed by dividing firm earnings by interest expenses.

Summary Statistics	All States		Bad State		Good State	
Variable	Mean	Std	Mean	Std	Mean	Std
$Total\ Assets\ (TA)$	197.1	17	163.96	12.8609	213.507	10.9017
$Investment$	0.0456	0.0063	0.0413	0.0067	0.0423	0.0052
$Asset\ Sales$	0.0176	0.0077	0.0175	0.006	0.0155	0.0079
q	1.472	0.0392	1.3994	0.0317	1.5087	0.0282
$Cov.\ Ratio$	2.0556	0.2036	1.9941	0.2230	2.0940	0.1756
$Leverage$	0.3942	0.0383	0.4454	0.0369	0.3679	0.0267
$Equity\ Value/TA$	0.6057	0.0383	0.5545	0.0369	0.6329	0.0264
$Equity\ Finance$	0.0279	0.0074	0.0237	0.007	0.0268	0.0077

The key properties of the simulated matched samples are structurally similar to our Compustat sample. As in our empirical sample (see Appendix 2, Table B1), firms in the simulated samples exhibit, on average, procyclical asset values, q, coverage ratios, and equity values. The average corporate leverage is countercyclical. The matched samples also exhibit several other structural features of the Compustat data. For instance, as in our Compustat sample, high q firms have on average a lower leverage and invest more than low q firms.

Next, we investigate in more detail the dynamics of equity financing and investments predicted by a typical simulation of a matched sample. Figure 4.6 shows the time series of the relative amount of firms that issue equity in the typical sample. The shaded areas represent bad states. Our model firms exhibit procyclical aggregate equity issuance patterns that correspond to well established findings in the empirical literature (e.g., Choe et al. 1993, Bayless and Caplinsky 1996).

Figure 4.6: **Aggregate Equity Financing.** This figure plots the aggregate ratio of firms in a typical simulated economy that issue equity over time. The shaded regions are bad states, and the white regions are good states.

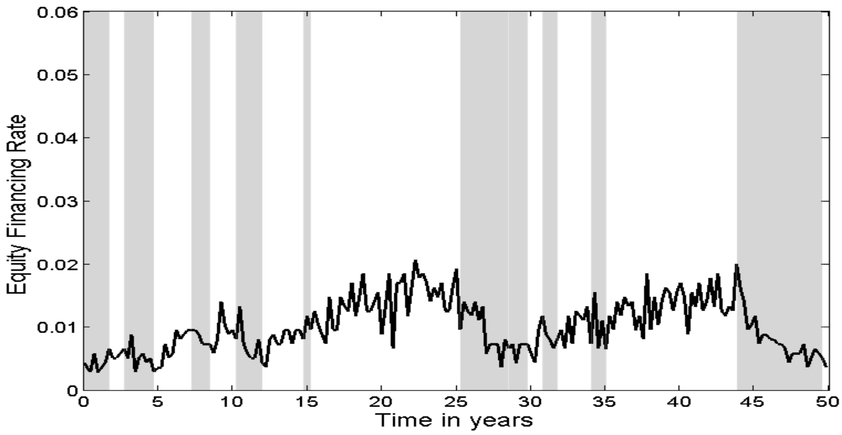


Figure 4.7 depicts the time series of the investment rate of the typical simulated matched sample. The investment rate is the fraction of firms that exercise their expansion option. The aggregate investment pattern is procyclical (see for corresponding evidence in the empirical investment literature e.g., Barro 1990, Cooper et al. 1999).

Figure 4.7: **Aggregate Investment.** This figure plots the aggregate ratio of firms in a typical simulated economy that invest over time. The shaded regions are bad states, and the white regions are good states.

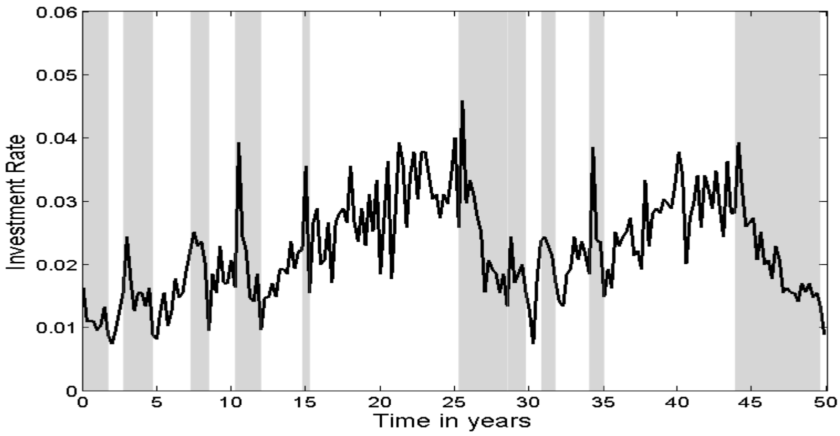
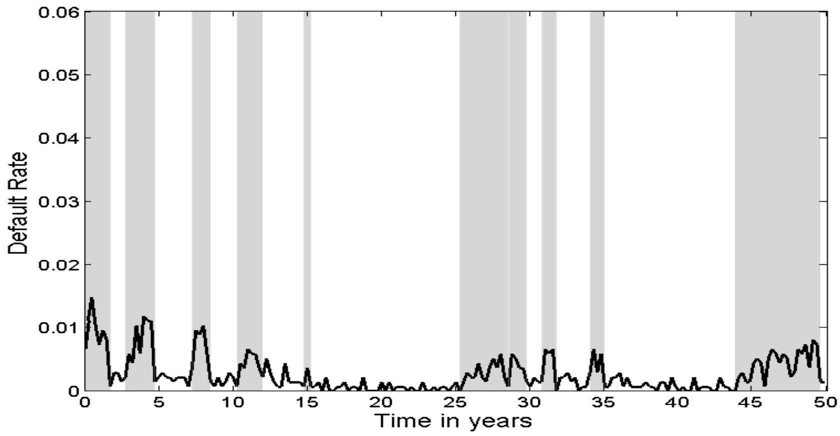


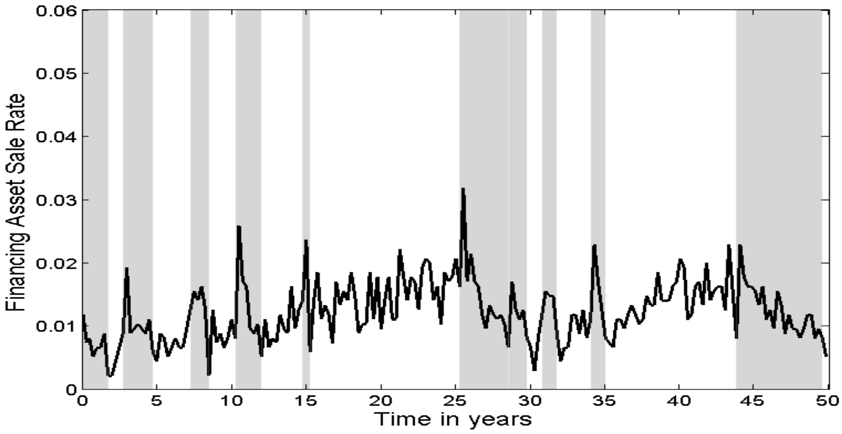
Figure 4.8 shows the time series of the aggregate default rate of the typical simulated sample. Aggregate defaults are countercyclical, and often spike in the beginning of a bad state. This pattern is consistent with empirical observations (see e.g., Duffie et al. 2007, Das et al. 2007).

Figure 4.8: **Aggregate Default.** This figure plots the aggregate ratio of firms in a typical simulated economy that default over time. The shaded regions are bad states, and the white regions are good states.



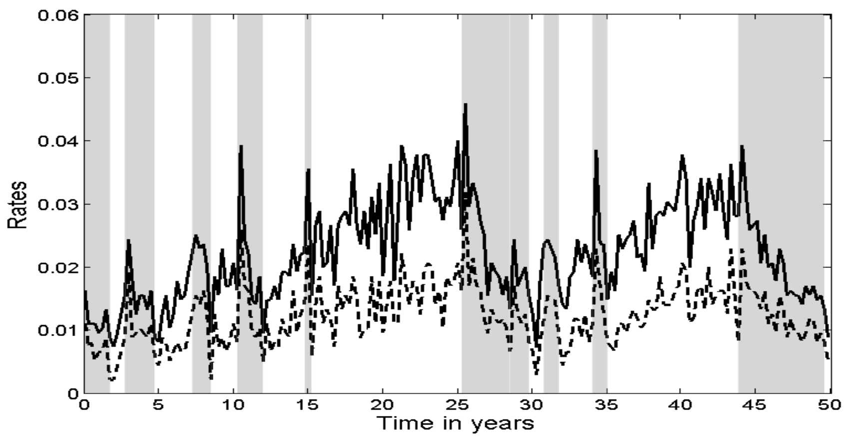
After verifying that the model features realistic sample properties, we now analyze the predictions of our model concerning the cyclical nature of financing asset sales. Figure 4.9 depicts the time series of the relative number of firms that sell assets to finance the exercise costs of the option in the typical simulated sample. Financing asset sales are generally procyclical, but often peak at those points in time at which the economy switches from a good to a bad state. The peaks occur because the investment threshold slightly decreases for firms with a less cyclical growth option when the business cycle switches from a good to a bad state, which leads to clustered investment of those firms with a current earnings level between the thresholds. As the propensity for financing asset sales is relatively large during bad states, the clustered investment of firms with a less cyclical growth option at the beginning of a bad state causes the peaks. Decreasing the proportion of firms with a less cyclical growth option reduces the peaks, and, hence, the investment rate during bad states. It does, however, not affect the relative propensity of firms to use financing asset sales during bad states.

Figure 4.9: **Aggregate Financing Asset Sales.** This figure plots the aggregate ratio of firms in a typical simulated economy that sell assets over time. The shaded regions are bad states, and the white regions are good states.



In Figure 4.10, we compare the time series of the investment rate (solid line) to the time series of the financing asset sales rate (dashed line) in the typical simulated sample. The distance between the dashed line and the solid line decreases during bad states, which indicates that asset sales are a relatively more important financing source for investment activities in bad states. Hence, Figure 4.10 illustrates that the aggregate dynamics of asset sales and investment across states generated by our model are consistent with our finding in the Compustat data that the correlation between asset sales and investment is significantly higher during bad business cycle states.

Figure 4.10: **Aggregate Investment and Financing Asset Sales.** This figure plots the aggregate ratio of firms in a typical simulated economy that invest (solid line), and the aggregate ratio of firms that sell assets (dashed line) over time. The shaded regions are bad states, and the white regions are good states.



In Table 4.4 we summarize additional features of the aggregate model dynamics of financing asset sales that corroborate our predictions from a typical firm at initiation. The conditional asset sale ratio is the percentage of firms in the simulated matched samples that, upon investment, finance the exercise costs of the option by selling assets. Since we do not have to be concerned about various sources of omitted variables or other determinants of asset sales in our simulated samples, we can directly use the conditional asset sale ratios to explain the correlation results we obtain in the Compustat sample. Overall, 47% of the investments in the simulated samples are financed with asset sales. If we only consider firms that are in the highest leverage tercile, this ratio increases to 54%. For firms in the lowest leverage tercile, the ratio decreases to 42%. The result that highly leveraged firms in the simulated matched samples have a higher tendency to use financing asset sales upon investment provides support to our model prediction 1, and to the finding in the Compustat data that the correlation between asset sales and investment increases in leverage.

In bad states, the conditional asset sale ratio increases to roughly 54%, and amounts to 43% in good states. This finding confirms our model prediction 2 that firms have a higher propensity to sell assets upon investment during bad states, which is also corroborated by the increased correlation between asset sales and investment during bad business cycle states in the real data.

Finally, we analyze which firms drive the high conditional asset sale ratio during bad times in our simulated samples. The last four rows in Table 4.4 report the asset sale ratios for firms in the simulated samples with a relatively low (L) and high (H) cyclicality of the expansion option during good and bad states, respectively. Firms with a low cyclicality have the highest ratio during bad business cycle states, which supports our model prediction 3, and explains the increased correlation between asset sales and investment for firms with less cyclical growth opportunities during the bad state in the real data.

Table 4.4: **Conditional Asset Sale Ratios**

The table provides summary statistics for conditional asset sale ratios from the simulated samples. Asset sale and investment are both dummy variables that are equal to one in case of an asset sale or an investment, respectively. To calculate conditional asset sale ratios, we aggregate over all simulations the asset sale and investment observations for the sample that we consider, and divide the sum of asset sale observations by the sum of investment observations. We compute this ratio for all firms, for firms in the highest and the lowest leverage terciles with resorting in every period, during bad and good states, and for firms with a more (H) or less (L) cyclical growth option. For details on the simulation see Section 4.6. L_{bad} and L_{good} are asset sale rates of firms with a low cyclicality of the expansion option during bad and good states, respectively. H_{bad} and H_{good} indicate the rates for firms with a high cyclicality in the two states.

Asset Sale Conditional on Investment	
Total Asset Sales	38.79%
High Leverage Firms	52.45%
Low Leverage Firms	35.34%
Bad States	43.77%
Good States	36.26%
L_{bad}	55.71%
L_{good}	42.82%
H_{bad}	51.81%
H_{good}	52.45%

4.7 Conclusion

In this paper, we analyze the decision of firms to sell assets to finance investments (financing asset sales). We derive and explain a novel aspect of this decision, that is, the relation between financing asset sales and the well-known wealth transfer problem between equityholders and debtholders at investment for firms with risky debt (Myers 1977). The model incorporates the impact of cyclicality on investment opportunities, financing decisions, and asset liquidity, which helps us to understand the drivers of financing asset sales.

The starting point of our work are empirical patterns of financing asset sales from a sample of U.S. Compustat firms. In the regression analysis, we focus on the correlation between asset sales and investment because it is unlikely that distressed firms tend to invest heavily in those periods, in which they are forced to sell assets to repay their debt. We explore the firm-specific and business cycle related variables that potentially drive this correlation. We find that the correlation between asset sales and investment is significantly higher (i) for firms with higher leverage, (ii) in bad business cycle states, (iii) for firms with a low cyclicality of the expansion option in bad business cycle states, and (iv) for unconstrained firms. Our empirical results cannot be explained by traditional motives for asset sales, such as financial distress or external financing constraints.

Against the backdrop of these stylized facts, we study a structural model with time-varying business cycle conditions, embedded inside a representative agent consumption-based asset pricing framework, that endogenizes the choice between asset sales and equity issuance to fund capital expenditures. Notably, equity issuance cost, asset liquidity, and the growth option are subject to cyclicality.

At investment, the decrease in the asset volatility and the increase in earnings make debt less risky and hence transfers value from equityholders to debtholders. This mechanism leads to the well-known wealth transfer problem that induces underinvestment. The results from our model show that the wealth transfer problem is exacerbated for firms with higher leverage because their debt is riskier and hence more sensitive to asset volatility and earnings changes.

On the other hand, selling assets upon investment increases leverage and hence makes debt riskier. The corresponding wealth transfer from debtholders to equityholders ameliorates the initial wealth transfer problem from the exercise of the expansion option. We show that the equityholders' trade off between the incremental friction cost of selling assets over the equity issuance cost and the reduction in the wealth transfer problem explains the empirical patterns we observe for financing asset sales in our Compustat sample.

We also examine the model's dynamic predictions by simulating model-implied firm samples over time that are structurally similar to our Compustat sample. The simulations generate investments, financing, and default patterns that are similar to the ones empirically observed. We also find that financing asset sales are procyclical, and often peak at those points in time at which the economy switches from a bad to a good state.

Overall, we contribute to identifying empirical and theoretical determinants of financing asset sales. In addition, we highlight the importance of cyclicality for explaining corporate financing and investment decisions. The observation that the wealth transfer problem can drive financing asset sales enriches our understanding of corporate financing decisions. To this end, our work suggests directions for further theoretical and empirical research. Future theoretical research could model to what extent managers use financing asset sales over the business cycle to maximize their personal utility. From an empirical perspective, the relationship between the wealth transfer problem and financing asset sales may help explain debt covenant structures observed in corporate practice.

Appendices

1 Derivations

1.1 The stochastic discount factor, risk-free rates, and market prices of risk

Suppose the continuous-time analog of Epstein-Zin-Weil preferences of stochastic differential utility type (e.g. Duffie and Epstein 1992a, Duffie and Epstein 1992b). The utility index U_t over a consumption process C_s solves

$$U_t = \mathbb{E}^{\mathbb{P}}\left[\int_t^\infty \frac{\rho}{1-\delta}\frac{C_s^{1-\delta} - ((1-\gamma)\,U_s)^{\frac{1-\delta}{1-\gamma}}}{((1-\gamma)\,U_s)^{\frac{1-\delta}{1-\gamma}} - 1}\mathrm{d}s\,|\mathcal{F}_t\right], \tag{A.1}$$

in which ρ determines the rate of time preference, γ is the coefficient of relative risk aversion for a timeless gamble, and $\Psi := \frac{1}{\delta}$ is the elasticity of intertemporal substitution for deterministic consumption paths. Incorporating the separability of time and state preferences and assuming that $\Psi > 1$, i.e., that agents have a preference for early resolution of uncertainty and require expected returns that increase in the uncertainty about future consumption, are necessary to capture the impact of aggregate risk on corporate security values.

Bhamra et al. (2010b) and Chen (2010) show that solving the Bellman equation associated with the consumption problem of the representative agent yields that the stochastic discount factor m_t follows the dynamics

$$\frac{\mathrm{d}m_t}{m_t} = -r_i\mathrm{d}t - \eta_i\mathrm{d}W_t^C + (e^{\kappa_i} - 1)\,\mathrm{d}M_t, \tag{A.2}$$

in which M_t determines the compensated process associated with the Markov chain. r_i are the regime-dependent risk-free interest rates. The parameters η_i denote the risk prices for systematic Brownian shocks affecting aggregate output. The market prices of consumption risk η_i increase in the agents' risk aversion and consumption volatility. κ_i are the relative jump sizes of the discount factor when the Markov chain leaves state i, i.e., they are the market prices of discount factor jump risk.

Risk-free rates, and the market prices of consumption and jump risk are defined as

$$\begin{aligned} r_i &= \bar{r}_i + \lambda_i \left[\frac{\gamma - \delta}{\gamma - 1} \left(w^{-\frac{\gamma-1}{\gamma-\delta}} - 1 \right) - \left(w^{-1} - 1 \right) \right], && \text{(A.3)} \\ \eta_i &= \gamma \sigma_i^C, && \text{(A.4)} \\ \kappa_i &= (\delta - \gamma) \log \left(\frac{h_j}{h_i} \right), && \text{(A.5)} \end{aligned}$$

with $i, j = G, B, i \neq j$. The parameters h_G, h_B solve the following non-linear system of equations (e.g. Bhamra et al. 2010b):

$$0 = \rho \Big(\frac{1-\gamma}{1-\delta} \Big) h_i^{\delta-\gamma} + \Big((1-\gamma)\,\theta_i - \tfrac{1}{2}\gamma\,(1-\gamma)\left(\sigma_i^C\right)^2 - \rho \frac{1-\gamma}{1-\delta} \Big) h_i^{1-\gamma} + \lambda_i \left(h_j^{1-\gamma} - h_i^{1-\gamma} \right) \tag{A.6}$$

The risk-free rates r_i consist of the interest rate if the economy stayed in regime i forever, $\bar{r}_i$, plus a second term adjusting for possible regime switches. The no-jump part of the interest rates, $\bar{r}_i$, are given by

$$\bar{r}_i = \rho + \delta\theta_i - \frac{1}{2}\gamma\,(1+\delta)\left(\sigma_i^C\right)^2, \tag{A.7}$$

and

$$w := e^{\kappa_B} = e^{-\kappa_G} \tag{A.8}$$

measures the size of the jump in the real-state price density when the economy shifts from bad states to good states (see, for example Proposition 1, Bhamra et al. 2010b).

1.2 Derivation of the values of corporate securities after investment

The valuation of corporate debt. Our valuation of corporate debt of a firm that consists of only invested assets in a two regime setting follows (Hackbarth et al. 2006). We consider the case in which the default boundary in good states is lower than the one in bad states, i.e., $\hat{D}_G < \hat{D}_B$. If the firm defaults, debtholders receive a fraction $\Lambda_i \alpha_i$ of the unleveraged after tax asset value $(1-\tau)Xy_i$. A debt investor requires an instantaneous return equal to the risk-free rate r_i. The instantaneous debt return corresponds to the realized rate of return plus the coupon proceeds from debt. Therefore, an application of Ito's lemma with regime switches shows that debt satisfies the following system of ODEs.

For $0 \leq X \leq \hat{D}_G$:

$$\begin{cases} \hat{d}_G(X) & = & \alpha_G \Lambda_G (1-\tau) X y_G \\ \hat{d}_B(X) & = & \alpha_B \Lambda_B (1-\tau) X y_B. \end{cases} \tag{A.9}$$

For $\hat{D}_G < X \leq \hat{D}_B$:

$$\begin{cases} r_G \hat{d}_G(X) & = & c + \tilde{\mu}_G X \hat{d}'_G(X) + \frac{1}{2}\tilde{\sigma}_G^2 X^2 \hat{d}''_G(X) + \tilde{\lambda}_G \left(\alpha_B \Lambda_B (1-\tau) X y_B - \hat{d}_G(X) \right) \\ \hat{d}_B(X) & = & \alpha_B \Lambda_B (1-\tau) X y_B. \end{cases} \tag{A.10}$$

For $X > \hat{D}_B$:

$$\begin{cases} r_G \hat{d}_G(X) & = & c + \tilde{\mu}_G X \hat{d}'_G(X) + \frac{1}{2}\tilde{\sigma}_G^2 X^2 \hat{d}''_G(X) + \tilde{\lambda}_G \left(\hat{d}_B(X) - \hat{d}_G(X) \right) \\ r_B \hat{d}_B(X) & = & c + \tilde{\mu}_B X \hat{d}'_B(X) + \frac{1}{2}\tilde{\sigma}_B^2 X^2 \hat{d}''_B(X) + \tilde{\lambda}_B \left(\hat{d}_G(X) - \hat{d}_B(X) \right). \end{cases} \tag{A.11}$$

The boundary conditions read

$$\lim_{X \to \infty} \frac{\hat{d}_i(X)}{X} < \infty, \quad i = G, B, \tag{A.12}$$

$$\lim_{X \searrow \hat{D}_B} \hat{d}_G(X) = \lim_{X \nearrow \hat{D}_B} \hat{d}_G(X), \tag{A.13}$$

$$\lim_{X \searrow \hat{D}_B} \hat{d}'_G(X) = \lim_{X \nearrow \hat{D}_B} \hat{d}'_G(X), \tag{A.14}$$

$$\lim_{X \searrow \hat{D}_G} \hat{d}_G(X) = \alpha_G \Lambda_G (1-\tau) D_G y_G, \tag{A.15}$$

and

$$\lim_{X \searrow \hat{D}_G} \hat{d}_B(X) = \alpha_B \Lambda_B (1-\tau) D_B y_B. \tag{A.16}$$

Condition (A.12) expresses the no-bubbles condition. The remaining boundary conditions are the value-matching conditions (A.13), (A.15), and (A.16), and the smooth-pasting condition at the higher default threshold $\hat{D}_B$ for the debt function in good state $\hat{d}_G(\cdot)$, Eq. (A.14). The functional form of the solution is

$$\hat{d}_i(X) = \begin{cases} \alpha_i \Lambda_i (1-\tau) X y_i & X \leq \hat{D}_i \qquad i = G, B \\ \hat{C}_1 X^{\beta_1^G} + \hat{C}_2 X^{\beta_2^G} + C_3 X + C_4 & \hat{D}_G < X \leq \hat{D}_B, \quad i = G \\ \hat{A}_{i1} X^{\gamma_1} + \hat{A}_{i2} X^{\gamma_2} + A_{i5} & X > \hat{D}_B, \qquad i = G, B, \end{cases} \tag{A.17}$$

in which $\hat{A}_{G1}, \hat{A}_{G2}, \hat{A}_{B1}, \hat{A}_{B2}, A_{G5}, A_{B5}, \hat{C}_1, \hat{C}_2, C_3, C_4, \gamma_1, \gamma_2, \beta_1^G$, and β_2^G are real-valued parameters to be determined.

First, consider the region $X > \hat{D}_B$. We start by using the standard approach of plugging the functional form $\hat{d}_i(X) = \hat{A}_{i1} X^{\gamma_1} + \hat{A}_{i2} X^{\gamma_2} + A_{i5}$ into both equations of (A.11). Comparing coefficients and solving the resulting two-dimensional system of equations for A_{i5}, we find that

$$A_{i5} = \frac{c\ (r_j + \tilde{\lambda}_i + \tilde{\lambda}_j)}{r_i r_j + r_j \tilde{\lambda}_i + r_i \tilde{\lambda}_j} = \frac{c}{r_i^p}, \tag{A.18}$$

and that $\hat{A}_{Gk}$ is always a multiple of $\hat{A}_{Bk}$, $k = 1, 2$, with the factor $l_k := \frac{1}{\tilde{\lambda}_G}(r_G + \tilde{\lambda}_G - \tilde{\mu}_G \gamma_k - \frac{1}{2}\tilde{\sigma}_G^2 \gamma_k(\gamma_k - 1))$, i.e., $\hat{A}_{Bk} = l_k \hat{A}_{Gk}$. Using these results when comparing coefficients again, it can be shown that γ_1 and γ_2 are the negative roots of the quadratic equation

$$(\tilde{\mu}_B \gamma + \tfrac{1}{2}\tilde{\sigma}_B^2 \gamma(\gamma - 1) - \tilde{\lambda}_B - r_B)(\tilde{\mu}_G \gamma + \tfrac{1}{2}\tilde{\sigma}_G^2 \gamma(\gamma - 1) - \tilde{\lambda}_G - r_G) = \tilde{\lambda}_B \tilde{\lambda}_G. \tag{A.19}$$

Due to the no-bubbles condition for debt stated in Eq. (A.12), we take the negative roots.

Next, we solve the region $\hat{D}_G \leq X \leq \hat{D}_B$. Plugging the functional form $d_G(X) = \hat{C}_1 X^{\beta_1^G} + \hat{C}_2 X^{\beta_2^G} + C_3 X + C_4$ into the first equation of (A.10), we find by comparison of coefficients that

$$\begin{aligned} \beta_{1,2}^G &= \frac{1}{2} - \frac{\tilde{\mu}_G}{\tilde{\sigma}_G^2} \pm \sqrt{\left(\frac{1}{2} - \frac{\tilde{\mu}_G}{\tilde{\sigma}_G^2}\right)^2 + \frac{2(r_G + \tilde{\lambda}_G)}{\tilde{\sigma}_G^2}} \\ C_3 &= \frac{\tilde{\lambda}_G \alpha_B \Lambda_B (1-\tau) y_B}{r_G + \tilde{\lambda}_G - \tilde{\mu}_G} \\ C_4 &= \frac{c}{r_G + \tilde{\lambda}_G}. \end{aligned} \tag{A.20}$$

We then plug the functional form (A.17) into conditions (A.13)–(A.16), and obtain a four-dimensional linear system in the remaining four unknown parameters $\hat{A}_{G1}, \hat{A}_{G2}, \hat{C}_1$, and

$\hat{C}_2$:

$$\begin{aligned}
\hat{A}_{G1}\hat{D}_B^{\gamma_1} + \hat{A}_{G2}\hat{D}_B^{\gamma_2} + A_{G5} &= \hat{C}_1\hat{D}_G^{\beta_1^G} + \hat{C}_2\hat{D}_B^{\beta_2^G} + C_3\hat{D}_B + C_4 \\
\hat{A}_{G1}\gamma_1\hat{D}_B^{\gamma_1} + \hat{A}_{G2}\gamma_2\hat{D}_B^{\gamma_2} &= \hat{C}_1\beta_1^G\hat{D}_B^{\beta_1^G} + \hat{C}_2\beta_2^G\hat{D}_B^{\beta_2^G} + C_3\hat{D}_B \\
\alpha_G\Lambda_G(1-\tau)\hat{D}_G y_G &= \hat{C}_1\hat{D}_B^{\beta_1^G} + \hat{C}_2\hat{D}_B^{\beta_2^G} + C_3\hat{D}_B + C_4 \\
l_1\hat{A}_{G1}\hat{D}_B^{\gamma_1} + l_2\hat{A}_{G2}\hat{D}_B^{\gamma_2} + A_{B5} &= \alpha_B\Lambda_B(1-\tau)\hat{D}_B y_B.
\end{aligned} \tag{A.21}$$

Define the matrices

$$\hat{M} := \begin{bmatrix} \hat{D}_B^{\gamma_1} & \hat{D}_B^{\gamma_2} & -\hat{D}_B^{\beta_1^G} & -\hat{D}_B^{\beta_2^G} \\ \gamma_1\hat{D}_B^{\gamma_1} & \gamma_2\hat{D}_B^{\gamma_2} & -\beta_1^G\hat{D}_B^{\beta_1^G} & -\beta_2^G\hat{D}_B^{\beta_2^G} \\ 0 & 0 & \hat{D}_B^{\beta_1^G} & \hat{D}_B^{\beta_2^G} \\ l_1\hat{D}_B^{\gamma_1} & l_2\hat{D}_B^{\gamma_2} & 0 & 0 \end{bmatrix} \tag{A.22}$$

and

$$\hat{b} := \begin{bmatrix} C_3\hat{D}_B + C_4 - A_{G5} \\ C_3\hat{D}_B \\ \alpha_G\Lambda_G(1-\tau)\hat{D}_G y_G - C_3\hat{D}_B - C_4 \\ \alpha_B\Lambda_B(1-\tau)\hat{D}_B y_B - A_{B5} \end{bmatrix}, \tag{A.23}$$

such that $\hat{M}\begin{bmatrix}\hat{A}_{G1} & \hat{A}_{G2} & \hat{C}_1 & \hat{C}_2\end{bmatrix}^T = \hat{b}$. The solution for the unknown parameters is given by

$$\begin{bmatrix}\hat{A}_{G1} & \hat{A}_{G2} & \hat{C}_1 & \hat{C}_2\end{bmatrix}^T = \hat{M}^{-1}\hat{b}. \tag{A.24}$$

The value of the tax shield can be calculated by the formula for the value of debt, in which c is replaced by τc, and α is equal to zero. The value of bankruptcy costs is simply obtained by replacing c by zero, and α by $1-\alpha$.

Default policy. The value of equity corresponds to the firm value minus the value of debt. The firm value is given by the value of assets in place plus the value of the option and the tax shield minus default costs. Once debt has been issued, managers select the ex post default policy that maximizes the value of equity. Formally, the default policy is determined by equating the first derivative of the equity value to zero at the corresponding default boundary:

$$\begin{cases} \hat{e}'_G(\hat{D}^*_G) &= 0 \\ \hat{e}'_B(\hat{D}^*_B) &= 0. \end{cases} \tag{A.25}$$

We solve this problem numerically.

Capital structure. Denote by $\hat{f}^*_i(X)$ the firm value of a firm with only invested assets, given optimal ex post default thresholds. The ex ante optimal coupon of a firm solves

$$\hat{c}^* := \text{argmax}_{\hat{c}} \hat{f}^*_i(X). \tag{A.26}$$

For a firm that receives scaled earnings after investment, the value of corporate securities is solved analogically by replacing X with the scaled level of earnings. For example, if the firm exercises the option in boom, and finances the exercise cost by issuing equity, the scaled earnings correspond to $(s_G + 1)X$. The default boundaries $\hat{D}^*_G$ and $\hat{D}^*_B$ are then expressed in terms of the scaled earnings levels.

1.3 Derivation of the value of the growth option

The case in which $X_G < X_B$:

We present the derivation of the value of the growth option for a firm that finances the option exercise by issuing equity in good states and selling assets in bad states. The value of the growth option for a firm with an alternative financing strategy can be derived analogically. For each regime i, the option is exercised immediately whenever $X \geq X_i$ (option exercise region); otherwise, it is optimal to wait (option continuation region). This structure results in the following system of ODEs for the value function.

For $0 \leq X < X_G$:

$$\begin{cases} r_G G_G(X) &= \tilde{\mu}_G X G'_G(X) + \frac{1}{2}\tilde{\sigma}^2_G X^2 G''_G(X) + \tilde{\lambda}_G \left(G_B(X) - G_G(X)\right) \\ r_B G_B(X) &= \tilde{\mu}_B X G'_B(X) + \frac{1}{2}\tilde{\sigma}^2_B X^2 G''_B(X) + \tilde{\lambda}_B \left(G_G(X) - G_B(X)\right). \end{cases} \tag{A.27}$$

For $X_G \leq X < X_B$:

$$\begin{cases} G_G(X) &= (1-\tau)s_G X y_G - K_G(1+\Upsilon_G) \\ r_B G_B(X) &= \tilde{\mu}_B X G'_B(X) + \frac{1}{2}\tilde{\sigma}_B^2 X^2 G''_B(X) + \tilde{\lambda}_B\left((1-\tau)s_G X y_G - K_B(1+\Upsilon_B) - G_B(X)\right). \end{cases} \tag{A.28}$$

For $X \geq X_B$:

$$\begin{cases} G_G(X) &= (1-\tau)s_G X y_G - K_G(1+\Upsilon_G) \\ G_B(X) &= (1-\tau)s_B X y_B - K_B/\Lambda_B. \end{cases} \tag{A.29}$$

Whenever the process X is in the option continuation region, which corresponds to system (A.27) and the second equation of (A.28), the required rate of return r_i (left-hand side) must be equal to the realized rate of return (right-hand side). The realized rate of return is calculated by applying Ito's lemma for regime switches. In this region, the last term captures the possible jump in the value of the growth option due to a regime switch. It can be expressed as the instantaneous probability of a regime shift, $\tilde{\lambda}_G$ or $\tilde{\lambda}_B$, times the associated change in the value of the option. The first equation of (A.28) and the system (A.29) state the payoff of the option at exercise. The process is in the option exercise region in these cases. The boundary conditions are given by

$$\lim_{X \searrow 0} G_i(X) = 0, \quad i = G, B, \tag{A.30}$$

$$\lim_{X \searrow X_G} G_B(X) = \lim_{X \nearrow X_G} G_B(X), \tag{A.31}$$

$$\lim_{X \searrow X_G} G'_B(X) = \lim_{X \nearrow X_G} G'_B(X), \tag{A.32}$$

$$\lim_{X \nearrow X_B} G_B(X) = (1-\tau)s_B X_B y_B - K_B/\Lambda_B, \tag{A.33}$$

and

$$\lim_{X \nearrow X_G} G_G(X) = (1-\tau)s_G X_G y_G - K_G(1+\Upsilon_G). \tag{A.34}$$

Condition (A.30) ensures that the option value goes to zero as earnings approach zero. Conditions (A.31) and (A.32) are the value-matching and smooth-pasting conditions of the value function bad times at the exercise boundary in good times. The remaining conditions (A.33)–(A.34) are the value-matching conditions at the exercise boundaries in a good state and a bad state, respectively.

The functional form of the solution is given by

$$G_i(X) = \begin{cases} \bar{A}_{i3}X^{\gamma_3} + \bar{A}_{i4}X^{\gamma_4} & 0 \le X < X_G, \quad i = G, B \\ \bar{C}_1 X^{\beta_1^B} + \bar{C}_2 X^{\beta_2^B} + \bar{C}_3 X + \bar{C}_4 & X_G \le X < X_B, \quad i = B \\ (1-\tau)s_B X y_B - K_B/\Lambda_B & X \ge X_B \quad\quad i = B \\ (1-\tau)s_G X y_G - K_G(1+\Upsilon_G) & X \ge X_G \quad\quad i = G \end{cases} \tag{A.35}$$

in which $\bar{A}_{G3}, \bar{A}_{G4}, \bar{A}_{B1}, \bar{A}_{B2}, \bar{C}_1, \bar{C}_2, \bar{C}_3, \bar{C}_4, \gamma_3, \gamma_4, \beta_1^B$, and β_2^B are real-valued parameters to be determined.

First, consider the region $0 \le X < X_G$, and plug the functional form $G_i(X) = \bar{A}_{i3}X^{\gamma_3} + \bar{A}_{i4}X^{\gamma_4}$ into both equations of (A.27). Comparison of coefficients shows that $\bar{A}_{Gk}$ is a multiple of $\bar{A}_{Bk}$, $k = 3, 4$, with the factor $\bar{l}_k := \frac{1}{\tilde{\lambda}_G}(r_G + \tilde{\lambda}_G - \tilde{\mu}_G\gamma_k - \frac{1}{2}\tilde{\sigma}_G^2\gamma_k(\gamma_k - 1))$, i.e., $\bar{A}_{Bk} = \bar{l}_k\bar{A}_{Gk}$. Using this result when comparing coefficients, we find that γ_3 and γ_4 correspond to the positive roots of the quadratic equation

$$(\tilde{\mu}_B\gamma + \frac{1}{2}\tilde{\sigma}_B^2\gamma(\gamma-1) - \tilde{\lambda}_B - r_B)(\tilde{\mu}_G\gamma + \frac{1}{2}\tilde{\sigma}_G^2\gamma(\gamma-1) - \tilde{\lambda}_G - r_G) = \tilde{\lambda}_B\tilde{\lambda}_G. \tag{A.36}$$

The reason for taking the positive roots is given by boundary condition (A.30).

Next, consider the region $X_G \le X < X_B$. Plugging the functional form $G_B(X) = \bar{C}_1X^{\beta_1} + \bar{C}_2X^{\beta_2} + \bar{C}_3X + \bar{C}_4$ into the second equation of (A.28), we find by comparison of coefficients that

$$\begin{aligned} \beta_{1,2}^B &= \frac{1}{2} - \frac{\tilde{\mu}_B}{\tilde{\sigma}_B^2} \pm \sqrt{\left(\frac{1}{2} - \frac{\tilde{\mu}_B}{\tilde{\sigma}_B^2}\right)^2 + \frac{2(r_B + \tilde{\lambda}_B)}{\tilde{\sigma}_B^2}}, \\ \bar{C}_3 &= \tilde{\lambda}_B \frac{(1-\tau)s_G y_G}{r_B - \tilde{\mu}_B + \tilde{\lambda}_B}, \\ \bar{C}_4 &= -\tilde{\lambda}_B \frac{K_B/\Lambda_B}{r_B + \tilde{\lambda}_B}. \end{aligned} \tag{A.37}$$

The remaining unknown parameters are $\bar{A}_{G3}, \bar{A}_{G4}, \bar{C}_1$, and $\bar{C}_2$. Plugging the functional form (A.35) into conditions (A.31)–(A.34) yields

$$\bar{C}_1 X_G^{\beta_1^B} + \bar{C}_2 X_G^{\beta_2^B} + \bar{C}_3 X_G + \bar{C}_4 = \bar{l}_3 \bar{A}_{G3} X_G^{\gamma_3} + \bar{l}_4 \bar{A}_{G4} X_G^{\gamma_4}, \tag{A.38}$$

$$\bar{C}_1 \beta_1^B X_G^{\beta_1^B} + \bar{C}_2 \beta_2^B X_G^{\beta_2^B} + \bar{C}_3 X_G = \bar{l}_3 \bar{A}_{G3} \gamma_3 X_G^{\gamma_3} + \bar{l}_4 \gamma_4 \bar{A}_{G4} X_G^{\gamma_4}, \tag{A.39}$$

$$\bar{C}_1 X_B^{\beta_1^B} + \bar{C}_2 X_B^{\beta_2^B} + \bar{C}_3 X_B + \bar{C}_4 = (1-\tau) s_B y_B X_B - K_B/\Lambda_B, \tag{A.40}$$

and

$$\bar{A}_{G3} X_G^{\gamma_3} + \bar{A}_{G4} X_G^{\gamma_4} = (1-\tau) s_G y_G X_G - K_G(1+\Upsilon_G). \tag{A.41}$$

This four-dimensional system is linear in its four unknowns $\bar{A}_{G3}, \bar{A}_{G4}, \bar{C}_1$ and $\bar{C}_2$. We define the matrices

$$\bar{M} := \begin{bmatrix} \bar{l}_3 X_G^{\gamma_3} & \bar{l}_4 X_G^{\gamma_4} & -X_G^{\beta_1^B} & -X_G^{\beta_2^B} \\ \bar{l}_3 \gamma_3 X_G^{\gamma_3} & \bar{l}_4 \gamma_4 X_G^{\gamma_4} & -\beta_1^B X_G^{\beta_1^B} & -\beta_2^B X_G^{\beta_2^B} \\ 0 & 0 & X_B^{\beta_1^B} & X_B^{\beta_2^B} \\ X_G^{\gamma_3} & X_G^{\gamma_4} & 0 & 0 \end{bmatrix}, \tag{A.42}$$

and

$$\bar{b} := \begin{bmatrix} \bar{C}_3 X_G + \bar{C}_4 \\ \bar{C}_3 X_G \\ -\bar{C}_3 X_B - \bar{C}_4 + (1-\tau) s_B y_B X_B - K_B/\Lambda_B \\ (1-\tau) s_G y_G X_G - K_G(1+\Upsilon_G) \end{bmatrix}, \tag{A.43}$$

such that $\bar{M} \begin{bmatrix} \bar{A}_{G3} & \bar{A}_{G4} & \bar{C}_1 & \bar{C}_2 \end{bmatrix}^T = \bar{b}$. The solution to the remaining four unknowns is given by

$$\begin{bmatrix} \bar{A}_{G3} & \bar{A}_{G4} & \bar{C}_1 & \bar{C}_2 \end{bmatrix}^T = \bar{M}^{-1} \bar{b}. \tag{A.44}$$

□

The unleveraged value of the growth option. The unleveraged value of the growth option is calculated by additionally imposing the smooth-pasting boundary conditions at option exercise:

$$\lim_{X \nearrow X_B^{unlev}} G_B^{unlev\prime}(X) = (1-\tau)s_B y_B \tag{A.45}$$

and

$$\lim_{X \nearrow X_G^{unlev}} G_G^{unlev\prime}(X) = (1-\tau)s_G y_G. \tag{A.46}$$

The solution method is analog to the one for the leveraged option value up to and including Eq. (A.37). System (A.38)–(A.41) is augmented by the two equations corresponding to the additional smooth-pasting boundary conditions:

$$\bar{C}_1^{unlev}\beta_1^B\left(X_B^{unlev}\right)^{\beta_1^B-1} + \bar{C}_2^{unlev}\beta_2^B\left(X_B^{unlev}\right)^{\beta_2^B-1} + \bar{C}_3 = (1-\tau)s_B y_B \tag{A.47}$$

and

$$\bar{A}_{G3}^{unlev}\gamma_3\left(X_G^{unlev}\right)^{\gamma_3-1} + \bar{A}_{G4}^{unlev}\gamma_4\left(X_G^{unlev}\right)^{\gamma_4-1} = (1-\tau)s_G y_G. \tag{A.48}$$

The full system is six-dimensional with the six unknowns $\bar{A}_{G3}^{unlev}, \bar{A}_{G4}^{unlev}, \bar{C}_1^{unlev}$, $\bar{C}_2^{unlev}$ X_G^{unlev}, and X_B^{unlev}, linear in the first four unknowns and nonlinear in the last two unknowns. It is solved numerically.

The case in which $X_G \geq X_B$:

The solution of the case $X_G \geq X_B$ can be obtained immediately by renaming regimes in the solution of the presented case for $X_G < X_B$.

1.4 Firms with invested assets and an expansion option

We first present a proof for the valuation of corporate debt in the case in which $D_G < D_B$, $\hat{D}_G < \hat{D}_B$, and $X_B > X_G$.

Proof of Proposition 2. An investor requires an instantaneous return equal to the risk-free rate r_i for holding corporate debt. The application of Ito's lemma with regime switches shows that debt must, consequently, satisfy the following system of ODEs.

For $0 \leq X \leq D_G$:

$$\left\{ \begin{array}{lcl} d_G(X) & = & \alpha_G \Lambda_G \left((1-\tau) X y_G + G_G^{unlev}(X) \right) \\ d_B(X) & = & \alpha_B \Lambda_B \left((1-\tau) X y_B + G_B^{unlev}(X) \right). \end{array} \right. \tag{A.49}$$

For $D_G < X \leq D_B$:

$$\left\{ \begin{array}{rcl} r_G d_G(X) & = & c + \tilde{\mu}_G X d_G'(X) + \frac{1}{2} \tilde{\sigma}_G^2 X^2 d_G''(X) \\ & & + \tilde{\lambda}_G \left(\alpha_B \Upsilon_B \left((1-\tau) X y_B + G_B^{unlev}(X) \right) - d_G(X) \right) \\ d_B(X) & = & \alpha_B \Lambda_B \left((1-\tau) X y_B + G_B^{unlev}(X) \right). \end{array} \right. \tag{A.50}$$

For $D_B < X < X_G$:

$$\left\{ \begin{array}{rcl} r_G d_G(X) & = & c + \tilde{\mu}_G X d_G'(X) + \frac{1}{2} \tilde{\sigma}_G^2 X^2 d_G''(X) + \tilde{\lambda}_G \left(d_B(X) - d_G(X) \right) \\ r_B d_B(X) & = & c + \tilde{\mu}_B X d_B'(X) + \frac{1}{2} \tilde{\sigma}_B^2 X^2 d_B''(X) + \tilde{\lambda}_B \left(d_G(X) - d_B(X) \right). \end{array} \right. \tag{A.51}$$

For $X_G \leq X < X_B$:

$$\left\{ \begin{array}{rcl} d_G(X) & = & \hat{d}_G\left((s_G+1) X \right) \\ r_B d_B(X) & = & c + \tilde{\mu}_B X d_B'(X) + \frac{1}{2} \tilde{\sigma}_B^2 X^2 d_B''(X) + \tilde{\lambda}_B \left(\hat{d}_G\left((s_G+1) X \right) - d_B(X) \right). \end{array} \right. \tag{A.52}$$

For $X \geq X_B$:

$$\left\{ \begin{array}{lcl} d_G(X) & = & \hat{d}_G\left((s_G+1) X \right) \\ d_B(X) & = & \hat{d}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau) X_{\bar{\imath}} y_B}) X \right). \end{array} \right. \tag{A.53}$$

In system (A.49), the firm is in the default region in both good states and bad times. In this region, debtholders receive $\alpha_i \Lambda_i \left((1-\tau) X y_i + G_i^{unlev}(X) \right)$ at default. The firm is in the continuation region in good state, and in the default region in bad states in system (A.50). For the continuation region in good states , the left-hand side of the first equation is the rate of return required by investors for holding corporate debt for one unit of time. The right-hand side is the realized rate of return, computed by Ito's lemma as the expected change in the value of debt plus the coupon payment c. The last term expresses the possible jump in the value of debt in case of a regime switch, that triggers immediate default. Eqs. (A.51) describe the case in which the firm is in the continuation region in both good and bad states. The next system, (A.52), treats the case in which the firm is in the exercise region in good states and in the continuation region in bad states. After exercising the option, the firm owns total assets in place with value $(1-\tau)Xy_i + (1-\tau)s_{\bar{i}}Xy_i$, reflecting the notion that the exercise cost of the growth option can be financed by issuing equity in good states. The value of debt must then be equal to the value of debt of a firm with only invested assets, i.e., $d_G(X) = \hat{d}_G((s_G+1)\,X)$, which is the first equation in (A.52). The second equation in this case is obtained by the same approach as in (A.51). The last term captures the notion that a regime switch from bad states to good states triggers immediate exercise of the expansion option with equity financing. Finally, (A.53) describes the case in which the firm is in the exercise region in both good and bad states. In the good states, the earnings of the firm are scaled by $s_G + 1$. In the bad states, the exercise cost K_B is financed by selling $\frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B}$ of the assets in place, such that the earnings of the firm are scaled by $(s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B})$.

The system is subject to the following boundary conditions.

$$\lim_{X\searrow D_B} d_G(X) = \lim_{X\nearrow D_B} d_G(X), \tag{A.54}$$

$$\lim_{X\searrow D_B} d'_G(X) = \lim_{X\nearrow D_B} d'_G(X), \tag{A.55}$$

$$\lim_{X\searrow D_G} d_G(X) = \alpha_G\Lambda_G\left((1-\tau)D_Gy_G + G_G^{unlev}(D_G)\right), \tag{A.56}$$

$$\lim_{X\searrow D_B} d_B(X) = \alpha_B\Lambda_B\left((1-\tau)D_By_B + G_B^{unlev}(D_B)\right), \tag{A.57}$$

$$\lim_{X\searrow X_G} d_B(X) = \lim_{X\nearrow X_G} d_B(X), \tag{A.58}$$

$$\lim_{X\searrow X_G} d'_B(X) = \lim_{X\nearrow X_G} d'_B(X), \tag{A.59}$$

$$\lim_{X\nearrow X_G} d_G(X) = \hat{d}_G((s_G+1)X_G), \tag{A.60}$$

and

$$\lim_{X\nearrow X_B} d_B(X_B) = \hat{d}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B})X_B\right). \tag{A.61}$$

Eqs. (A.54) and (A.55) are the value-matching and smooth-pasting conditions for the debt value in the good state at the default boundary of the bad state. Eqs. (A.58) and (A.59) are the corresponding conditions for the debt value in the bad state at the option exercise boundary of the good state. Eqs. (A.56) and (A.57) show the value-matching conditions at the default thresholds, and Eqs. (A.60) and (A.61) are the value-matching conditions at the option exercise boundaries. The default thresholds and option exercise boundaries are chosen by equity-holders. Hence, we do not have the corresponding smooth-pasting conditions for debt.

To solve this system, we start with the functional form of the solution, in which $A_{G1}, A_{G2}, A_{B1}, A_{B2}, C_1, C_2, C_3, C_4, C_5, C_6, B_1, B_2, B_4, \beta_1^G, \beta_2^G, \beta_1^B, \beta_2^B, \gamma_1, \gamma_2, \gamma_3$, and γ_4 are real-valued parameters to be determined (or to be confirmed).

We first consider the region $D_B < X \leq X_G$. Plugging the functional form $d_i(X) = A_{i1}X^{\gamma_1} + A_{i2}X^{\gamma_2} + A_{i3}X^{\gamma_3} + A_{i4}X^{\gamma_4} + A_{i5}$ into both equations of (A.51) and comparing coefficients, we find that

$$A_{i5} = \frac{c(r_j + \tilde{\lambda}_i + \tilde{\lambda}_j)}{r_i r_j + r_j \tilde{\lambda}_i + r_i \tilde{\lambda}_j} = \frac{c}{r_i^p}. \tag{A.62}$$

As in 1.2, A_{Gk} is always a multiple of A_{Bk}, $k = 1, \ldots, 4$, with the factor $l_k := \frac{1}{\tilde{\lambda}_G}(r_G + \tilde{\lambda}_G - \tilde{\mu}_G \gamma_k - \frac{1}{2}\tilde{\sigma}_G^2 \gamma_k(\gamma_k - 1))$, i.e., $A_{Bk} = l_k A_{Gk}$. Using this relation and comparing coefficients, it can be shown that $\gamma_1, \gamma_2, \gamma_3$, and γ_4 correspond to the roots of the quadratic equation

$$(\tilde{\mu}_B \gamma + \tfrac{1}{2}\tilde{\sigma}_B^2 \gamma(\gamma - 1) - \tilde{\lambda}_B - r_B)(\tilde{\mu}_G \gamma + \tfrac{1}{2}\tilde{\sigma}_G^2 \gamma(\gamma - 1) - \tilde{\lambda}_G - r_G) = \tilde{\lambda}_B \tilde{\lambda}_G. \tag{A.63}$$

According to (Guo 2001), this quadratic equation always has two negative and two positive distinct real roots. The value of debt in both regimes is subject to boundary conditions from below (default) and above (exercise of expansion option). To meet all boundary conditions, we use four terms with the corresponding factors A_{ik} as well as the exponents γ_k, which requires the usage of all four roots of Eq. (A.63). The no-bubbles condition is not considered again because it is already implemented in the value function $\hat{d}_i$ of a firm with only invested assets. The unknown parameters for this region are $A_{Gk},\ k = 1, \ldots, 4$.

Next, we examine the region $D_G \leq X \leq D_B$. Plugging the functional form $d_G(X) = C_1 X^{\beta_1^G} + C_2 X^{\beta_2^G} + C_3 X + C_4 + C_5 X^{\gamma_3} + C_6 X^{\gamma_4}$ into the second equation of (A.50), we find by comparison of coefficients that

$$\beta_{1,2}^{G} = \frac{1}{2} - \frac{\tilde{\mu}_G}{\tilde{\sigma}_G^2} \pm \sqrt{\left(\frac{1}{2} - \frac{\tilde{\mu}_G}{\tilde{\sigma}_G^2}\right)^2 + \frac{2(r_G + \tilde{\lambda}_G)}{\tilde{\sigma}_G^2}}, \tag{A.64}$$

$$C_3 = \tilde{\lambda}_G \frac{\alpha_B \Lambda_B (1-\tau) y_B}{r_G + \tilde{\lambda}_G - \tilde{\mu}_G}, \tag{A.65}$$

$$C_4 = \frac{c}{r_G + \tilde{\lambda}_G}, \tag{A.66}$$

$$C_5 = \alpha_B \Lambda_B \frac{\bar{l}_3}{l_3} \bar{A}_{G3}^{unlev}, \tag{A.67}$$

and

$$C_6 = \alpha_B \Lambda_B \frac{\bar{l}_4}{l_4} \bar{A}_{G4}^{unlev}. \tag{A.68}$$

The unknown parameters remaining in this region are C_1 and C_2.

Finally, we consider the region $X_G < X \leq X_B$. Plugging the functional form $B_1 X^{\beta_1^B} + B_2 X^{\beta_2^B} + Z(X) + \tilde{\lambda}_B \frac{c}{r_i^P (r_B + \tilde{\lambda}_B)} + \frac{c}{r_B + \tilde{\lambda}_B}$ into the second equation of (A.52) and comparing coefficients, we find that

$$Z(X) = \tilde{\lambda}_B B_5 X^{\gamma_1} + \tilde{\lambda}_B B_6 X^{\gamma_2}. \tag{A.69}$$

$$\tag{A.70}$$

The parameters B_5 and B_6 are given by

$$B_5 = \frac{(s_B + 1)^{\gamma_1} \hat{A}_{G1}}{r_B - \tilde{\mu}_B \gamma_1 - \frac{1}{2}\tilde{\sigma}_B^2 \gamma_1 (\gamma_1 - 1) + \tilde{\lambda}_B}, \tag{A.71}$$

and

$$B_6 = \frac{(s_B + 1)^{\gamma_2} \hat{A}_{G2}}{r_B - \tilde{\mu}_B \gamma_2 - \frac{1}{2}\tilde{\sigma}_B^2 \gamma_2 (\gamma_2 - 1) + \tilde{\lambda}_B}. \tag{A.72}$$

The unknown parameters remaining in this region are B_1 and B_2.

To solve for the unknown parameters $A_{G1}, A_{G2}, A_{G3}, A_{G4}, C_1, C_2, B_1$, and B_2, we plug the functional form (4.4.8) into the system of boundary conditions (A.54)–(A.61):

$$
\begin{aligned}
\sum_{k=1}^{4} A_{Gk} D_B^{\gamma_k} + A_{G5} &= C_1 D_B^{\beta_1^G} + C_2 D_B^{\beta_2^G} + C_3 X + C_4 + C_5 X^{\gamma_3} + C_6 X^{\gamma_4} \\
\sum_{k=1}^{4} A_{Gk} \gamma_k D_B^{\gamma_k} &= C_1 \beta_1^G D_B^{\beta_1^G} + C_2 \beta_2^G D_B^{\beta_2^G} + C_3 X + C_5 \gamma_3 X^{\gamma_3} + C_6 \gamma_4 X^{\gamma_4} \\
\alpha_G \Lambda_G \Big((1+\tau) D_G y_G + G_G^{unlev}(D_G) \Big) &= C_1 D_G^{\beta_1^G} + C_2 D_G^{\beta_2^G} + C_3 D_G + C_4 + C_5 D_G^{\gamma_3} + C_6 D_G^{\gamma_4} \\
\sum_{k=1}^{4} l_k A_{Gk} D_B^{\gamma_k} + A_{B5} &= \alpha_B \Lambda_B \Big((1+\tau) D_B y_B + G_B^{unlev}(D_B) \Big) \\
\sum_{k=1}^{4} l_k A_{Gk} X_G^{\gamma_k} + A_{B5} &= B_1 X_G^{\beta_1^B} + B_2 X_G^{\beta_2^B} + Z(X_G) + B_4 \qquad \text{(A.73)} \\
\sum_{k=1}^{4} l_k A_{Gk} \gamma_k X_G^{\gamma_k} &= B_1 \beta_1^B X_G^{\beta_1^B} + B_2 \beta_2^B X_G^{\beta_2^B} + X_G Z'(X_G) \\
\sum_{k=1}^{4} A_{Gk} X_G^{\gamma_k} + A_{G5} &= \hat{d}_G \left((s_G + 1) X_G \right) \\
B_1 X_B^{\beta_1^B} + B_2 X_B^{\beta_2^B} + Z(X_B) + B_4 &= \hat{d}_B \left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau) X_{\bar{t}} y_B}) X_B \right).
\end{aligned}
$$

Using matrix notation, we can write

$$
M := \begin{bmatrix}
D_B^{\gamma_1} & D_B^{\gamma_2} & D_B^{\gamma_3} & D_B^{\gamma_4} & -D_B^{\beta_1^G} & -D_B^{\beta_2^G} & 0 & 0 \\
\gamma_1 D_B^{\gamma_1} & \gamma_2 D_B^{\gamma_2} & \gamma_3 D_B^{\gamma_3} & \gamma_4 D_B^{\gamma_4} & -\beta_1^G D_B^{\beta_1^G} & -\beta_2^G D_B^{\beta_2^G} & 0 & 0 \\
0 & 0 & 0 & 0 & D_G^{\beta_1^G} & D_G^{\beta_2^G} & 0 & 0 \\
l_1 D_B^{\gamma_1} & l_2 D_B^{\gamma_2} & l_3 D_B^{\gamma_3} & l_4 D_B^{\gamma_4} & 0 & 0 & 0 & 0 \\
l_1 X_G^{\gamma_1} & l_2 X_G^{\gamma_2} & l_3 X_G^{\gamma_3} & l_4 X_G^{\gamma_4} & 0 & 0 & -X_G^{\beta_1^B} & -X_G^{\beta_2^B} \\
l_1 \gamma_1 X_G^{\gamma_1} & l_2 \gamma_2 X_G^{\gamma_2} & l_3 \gamma_3 X_G^{\gamma_3} & l_4 \gamma_4 X_G^{\gamma_4} & 0 & 0 & -\beta_1^B X_G^{\beta_1^B} & -\beta_2^B X_G^{\beta_2^B} \\
X_G^{\gamma_1} & X_G^{\gamma_2} & X_G^{\gamma_3} & X_G^{\gamma_4} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & X_B^{\beta_1^B} & X_B^{\beta_2^B}
\end{bmatrix}
\qquad \text{(A.74)}
$$

and

$$b := \begin{bmatrix} -A_{G5} + C_3 D_B + C_4 + C_5 D_B^{\gamma_1} + C_6 D_B^{\gamma_2} \\ C_3 D_B + \gamma_1 C_5 D_B^{\gamma_1} + \gamma_2 C_6 D_B^{\gamma_2} \\ -C_3 D_G - C_4 - C_5 D_G^{\gamma_3} - C_6 D_G^{\gamma_4} + \alpha_G \Lambda_G \left((1-\tau) D_G y_G + G_G^{unlev}(D_G)\right) \\ -A_{B5} + \alpha_B \Lambda_B \left((1-\tau) D_B y_B + G_B^{unlev}(D_B)\right) \\ -A_{B5} + Z\left(X_G\right) + B_4 \\ X_G Z'\left(X_G\right) \\ -A_{G5} + \hat{d}_G\left((s_G+1) X_G\right) \\ -Z\left(X_B\right) + B_4 + \hat{d}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau) X_{\bar{t}} y_B}) X_B\right) \end{bmatrix}. \tag{A.75}$$

The solution to the remaining unknowns is now given by

$$\begin{bmatrix} A_{G1} & A_{G2} & A_{G3} & A_{G4} & C_1 & C_2 & B_1 & B_2 \end{bmatrix}^T = M^{-1} b. \tag{A.76}$$

$\square$

The case in which $D_G < D_B$, $\hat{D}_G < \hat{D}_B$, and $X_G > X_B$:

Going through the same steps as in the previous case gives us

$$M := \begin{bmatrix} D_B^{\gamma_1} & D_B^{\gamma_2} & D_B^{\gamma_3} & D_B^{\gamma_4} & -D_B^{\beta_1^G} & -D_B^{\beta_2^G} & 0 & 0 \\ \gamma_1 D_B^{\gamma_1} & \gamma_2 D_B^{\gamma_2} & \gamma_3 D_B^{\gamma_3} & \gamma_4 D_B^{\gamma_4} & -\beta_1^G D_B^{\beta_1^G} & -\beta_2^G D_B^{\beta_2^G} & 0 & 0 \\ 0 & 0 & 0 & 0 & D_G^{\beta_1^G} & D_G^{\beta_2^G} & 0 & 0 \\ l_1 D_B^{\gamma_1} & l_2 D_G^{\gamma_2} & l_3 D_B^{\gamma_3} & l_4 D_B^{\gamma_4} & 0 & 0 & 0 & 0 \\ X_B^{\gamma_1} & X_B^{\gamma_2} & X_B^{\gamma_3} & X_B^{\gamma_4} & 0 & 0 & -X_B^{\beta_1^G} & -X_B^{\beta_2^G} \\ \gamma_1 X_B^{\gamma_1} & \gamma_2 X_B^{\gamma_2} & \gamma_3 X_B^{\gamma_3} & \gamma_4 X_B^{\gamma_4} & 0 & 0 & -\beta_1^G X_B^{\beta_1^G} & -\beta_2^G X_B^{\beta_2^G} \\ l1 X_B^{\gamma_1} & l2 X_B^{\gamma_2} & l3 X_B^{\gamma_3} & l4 X_B^{\gamma_4} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & X_G^{\beta_1^G} & X_G^{\beta_2^G} \end{bmatrix} \tag{A.77}$$

and

$$b := \begin{bmatrix} -A_{G5} + C_3 D_B + C_4 + C_5 D_B^{\gamma_1} + C_6 D_B^{\gamma_2} \\ C_3 D_B + \gamma_1 C_5 D_B^{\gamma_1} + \gamma_2 C_6 D_B^{\gamma_2} \\ -C_3 D_G - C_4 - C_5 D_G^{\gamma_3} - C_6 D_G^{\gamma_4} + \alpha_G \Lambda_G \left((1-\tau) D_G y_G + G_G^{unlev}(D_G)\right) \\ -A_{B5} + \alpha_B \Lambda_B \left((1-\tau) D_B y_B + G_B^{unlev}(D_B)\right) \\ -A_{G5} + Z\left(X_B\right) + B_4 \\ X_B Z'\left(X_B\right) \\ -A_{B5} + \hat{d}_B \left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}} y_B}) X_B\right) \\ -Z\left(X_G\right) + B_4 + \hat{d}_G\left((s_G+1)X_G\right) \end{bmatrix}. \tag{A.78}$$

The solution to the unknowns is again given by

$$\begin{bmatrix} A_{G1} & A_{G2} & A_{G3} & A_{G4} & C_1 & C_2 & B_1 & B_2 \end{bmatrix}^T = M^{-1} b. \tag{A.79}$$

1.5 Bankruptcy costs

For the calculation of bankruptcy costs, the ODEs are given by the following system:

For $0 \leq X \leq D_G$:

$$\begin{cases} b_G\left(X\right) &= (1-\alpha_G\Lambda_G)(1-\tau)X y_G + G_G\left(X\right) - \alpha_G\Lambda_G G_G^{unlev}\left(X\right) \\ b_B\left(X\right) &= (1-\alpha_B\Lambda_B)(1-\tau)X y_B + G_B\left(X\right) - \alpha_B\Lambda_B B_B^{unlev}\left(X\right). \end{cases} \tag{A.80}$$

For $D_G < X \leq D_B$:

$$\begin{cases} r_G b_G\left(X\right) &= \tilde{\mu}_G X b_G'\left(X\right) + \frac{1}{2}\tilde{\sigma}_G^2 X^2 b_G''\left(X\right) \\ & \quad + \tilde{\lambda}_G\left((1-\alpha_B\Lambda_B)(1-\tau)X y_B + G_B\left(X\right) - \alpha_B\Lambda_B G_B^{unlev}\left(X\right) - b_G\left(X\right)\right) \\ b_B\left(X\right) &= (1-\alpha_B\Lambda_B)\left(1-\tau\right)X y_B + G_B\left(X\right) - \alpha_B\Lambda_B G_B^{unlev}\left(X\right). \end{cases} \tag{A.81}$$

For $D_B < X < X_G$:

$$\begin{cases} r_G d_G(X) &= c + \tilde{\mu}_G X b'_G(X) + \frac{1}{2}\tilde{\sigma}_G^2 X^2 b''_G(X) + \tilde{\lambda}_G (b_B(X) - b_G(X)) \\ r_B d_B(X) &= c + \tilde{\mu}_B X d'_B(X) + \frac{1}{2}\tilde{\sigma}_B^2 X^2 b''_B(X) + \tilde{\lambda}_B (b_G(X) - b_B(X)) . \end{cases} \tag{A.82}$$

For $X_G \leq X < X_B$:

$$\begin{cases} b_G(X) &= \hat{d}_G((s_G+1)X) \\ r d_B(X) &= c + \tilde{\mu}_B X b'_B(X) + \frac{1}{2}\tilde{\sigma}_B^2 X^2 b''_B(X) + \tilde{\lambda}_B \left(\hat{d}_G((s_G+1)X) - b_B(X)\right) . \end{cases} \tag{A.83}$$

For $X \geq X_B$:

$$\begin{cases} b_G(X) &= \hat{b}_G((s_G+1)X) \\ b_B(X) &= \hat{b}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B})X\right) . \end{cases} \tag{A.84}$$

The boundary conditions are as follows:

$$\lim_{X \searrow D_B} b_G(X) = \lim_{X \nearrow D_B} b_G(X) , \tag{A.85}$$

$$\lim_{X \searrow D_B} b'_G(X) = \lim_{X \nearrow D_B} b'_G(X) , \tag{A.86}$$

$$\lim_{X \searrow D_G} b_G(X) = (1 - \alpha_G \Lambda_B)(1-\tau) D_G y_G + G_G(D_G) - \alpha_G \Lambda_G G_G^{unlev}(D_G) , \tag{A.87}$$

$$\lim_{X \searrow D_B} b_B(X) = (1 - \alpha_G \Lambda_G)(1-\tau) D_B y_B + G_B(D_B) - \alpha_B G_B^{unlev}(D_B) , \tag{A.88}$$

$$\lim_{X \searrow X_G} b_B(X) = \lim_{X \nearrow X_G} b_B(X) , \tag{A.89}$$

$$\lim_{X \searrow X_G} b'_B(X) = \lim_{X \nearrow X_G} b'_B(X) , \tag{A.90}$$

$$\lim_{X \nearrow X_G} b_G(X) = \hat{b}_G((s_G+1)X_G) , \tag{A.91}$$

and

$$\lim_{X \nearrow X_B} b_B(X_B) = \hat{b}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}}y_B})X_B\right) . \tag{A.92}$$

Eqs. (A.85) and (A.86) are the value-matching and smooth-pasting conditions for bankruptcy costs in good states at the default boundary in bad states. Similarly, Eqs. (A.89) and (A.90) are the corresponding conditions for bankruptcy costs in bad states at the option exercise boundary in good states. Eqs. (A.87) and (A.88) are the value-matching conditions at the default thresholds. They incorporate the fact that upon default, the value of the leveraged growth option switches to the value of the unleveraged growth option. Eqs. (A.91) and (A.92) are the value-matching conditions at the option exercise boundaries.

To solve for the unknown parameters, we plug the functional form

$$b_i(X) = \begin{cases} (1-\alpha_i\Lambda_i)(1-\tau)Xy_i - \alpha_i\Lambda_i G_i^{unlev}(X) + G_i(X) & X \leq D_i, \quad i = G, B \\ C_1 X^{\beta_1^B} + C_2 X^{\beta_2^B} + C_5 X^{\gamma_3} + C_6 X^{\gamma_4} & \\ \quad + \tilde{\lambda}_G \frac{\alpha_B \Lambda_B y_B (1-\tau)}{r_G - \tilde{\mu}_G + \tilde{\lambda}_G} X + \frac{c}{r_G + \tilde{\lambda}_G} & D_G < X \leq D_B, \quad i = G \\ A_{i1} X^{\gamma_1} + A_{i2} X^{\gamma_2} + A_{i3} X^{\gamma_3} + A_{i4} X^{\gamma_4} + \frac{c}{r_i^P} & D_B < X \leq X_G, \quad i = G, B \\ B_1 X^{\beta_1^B} + B_2 X^{\beta_2^B} + Z(X) + \tilde{\lambda}_B \frac{c}{r_i^P\left(r_B + \tilde{\lambda}_B\right)} + \frac{c}{r_B + \tilde{\lambda}_B} & X_G < X \leq X_B, \quad i = B \\ \hat{b}_G\left((s_G+1)X\right) & X > X_G, \quad i = G \\ \hat{b}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}} y_B})X\right) & X > X_B, \quad i = B \end{cases} \tag{A.93}$$

into the system of boundary conditions (A.85)-(A.92). The solution to the unknowns is given by

$$\begin{bmatrix} A_{G1} & A_{G2} & A_{G3} & A_{G4} & C_1 & C_2 & B_1 & B_2 \end{bmatrix}^T = M^{-1} b, \tag{A.94}$$

where

$$M := \begin{bmatrix} D_B^{\gamma_1} & D_B^{\gamma_2} & D_B^{\gamma_3} & D_B^{\gamma_4} & -D_B^{\beta_1^G} & -D_B^{\beta_2^G} & 0 & 0 \\ \gamma_1 D_B^{\gamma_1} & \gamma_2 D_B^{\gamma_2} & \gamma_3 D_B^{\gamma_3} & \gamma_4 D_B^{\gamma_4} & -\beta_1^G D_B^{\beta_1^G} & -\beta_2^G D_B^{\beta_2^G} & 0 & 0 \\ 0 & 0 & 0 & 0 & D_G^{\beta_1^G} & D_G^{\beta_2^G} & 0 & 0 \\ l_1 D_B^{\gamma_1} & l_2 D_B^{\gamma_2} & l_3 D_B^{\gamma_3} & l_4 D_B^{\gamma_4} & 0 & 0 & 0 & 0 \\ l_1 X_G^{\gamma_1} & l_2 X_G^{\gamma_2} & l_3 X_G^{\gamma_3} & l_4 X_G^{\gamma_4} & 0 & 0 & -X_G^{\beta_1^B} & -X_G^{\beta_2^B} \\ l_1\gamma_1 X_G^{\gamma_1} & l_2\gamma_2 X_G^{\gamma_2} & l_3\gamma_3 X_G^{\gamma_3} & l_4\gamma_4 X_G^{\gamma_4} & 0 & 0 & -\beta_1^B X_G^{\beta_1^B} & -\beta_2^B X_G^{\beta_2^B} \\ X_G^{\gamma_1} & X_G^{\gamma_2} & X_G^{\gamma_3} & X_G^{\gamma_4} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & X_B^{\beta_1^B} & X_B^{\beta_2^B} \end{bmatrix}, \tag{A.95}$$

$$b := \begin{bmatrix} -A_{G5} + C_3 D_B + C_4 + C_5 D_B^{\gamma_1} + C_6 D_B^{\gamma_2} \\ C_3 D_B + \gamma_1 C_5 D_B^{\gamma_1} + \gamma_2 C_6 D_B^{\gamma_2} \\ -C_3 D_G - C_4 - C_5 D_G^{\gamma_3} - C_6 D_G^{\gamma_4} + (1-\alpha_G\Lambda_G)\left((1-\tau)D_G y_G - \alpha_G\Lambda_G G_G^{unlev}(D_G)\right) + G_G(D_G) \\ -A_{B5} + (1-\alpha_B\Lambda_B)\left((1-\tau)D_B y_B - \alpha_B\Lambda_B G_B^{unlev}(D_B)\right) + G_B(D_B) \\ -A_{B5} + Z\left(X_G\right) + B_4 \\ X_G Z'\left(X_G\right) \\ -A_{G5} + \hat{d}_G\left((s_G+1)X_G\right) \\ -Z\left(X_B\right) + B_4 + \hat{d}_B\left((s_B + 1 - \frac{K_B/\Lambda_B}{(1-\tau)X_{\bar{t}} y_B})X_B\right) \end{bmatrix}, \tag{A.96}$$

$$C_5 = \frac{\bar{l}_3}{l_3}\left(\bar{A}_{G3}^{lev} - \alpha_B\Lambda_B\bar{A}_{G3}^{unlev}\right), \tag{A.97}$$

and

$$C_6 = \frac{\bar{l}_4}{l_4}\left(\bar{A}_{G4}^{lev} - \alpha_B\Lambda_B\bar{A}_{G4}^{unlev}\right). \tag{A.98}$$

The case in which $D_G < D_B$, $\hat{D}_G < \hat{D}_B$, and $X_G > X_B$:

This case can be solved analogously.

2 Data and Variables

Our sample includes all U.S. manufacturing firms (SIC codes between 2000 and 3999) as provided in the Compustat annual research file. We consider the following firm individual variables: F_t are the net fixed assets (PPENT) at the beginning of the period t, and $Total\ Assets$ are the book values of the assets (AT). $Asset\ Sale$ is equal to the cash proceeds received from the sale of fixed assets (SPPE), and $Investment$ is obtained from the Compustat item capital expenditures (CAPX). Both variables are scaled by F_t. We compute the firm individual sales growth as first difference of the Compustat item SALE. We standardize the firm individual sales growth by subtracting the mean and scaling it with its standard deviation. To compute the sample aggregate sales growth we compute then for each year the value-weighted mean sales growth across all sample firms. Age is the number of years a firm has been listed at the NYSE/AMEX/NASDAQ, i.e., the current year minus the first year of a firm's stock price entry in the merged CRSP/Compustat file. Using $Total\ Assets$ and Age, we construct the SA-index as measure of financial constraints following Hadlock and Pierce (2010) as

$$-0.737 * Total\ Assets + 0.043 * (Total\ Assets)^2 - 0.04 * Age. \tag{B.1}$$

q is a proxy for growth opportunities and calculated as the sum of total debt and market equity divided by the book value of total assets (cf., Hovakimian and Titman 2006). $Financial\ Slack$ corresponds to the sum of cash and short-term investments (CHE) scaled by F_t. We define $Total\ Debt$ as the sum of total liabilities (LT) and total preferred stock (PSTK) excluding deferred taxes (TXDB) and convertible debt (DCVT) scaled by $Total\ Assets$. As a proxy for $Cash\ Flow$ we use the sum of income before extraordinary items, depreciation and amortization (IB + DP) scaled by F_t. $Cov.\ Ratio$ is EBITDA divided by interest expenses (XINT). The Altman (1968) Z-score is a widely used measure of financial distress. It is computed for each firm as

$$Z = 1.2 * \frac{ACT - LCT}{AT} + 1.4 * \frac{RE}{AT} + 3.3 * \frac{NI + XINT + TXT}{AT} + 0.6 * \frac{ME}{LT} + 0.999 * \frac{SALE}{AT}. \tag{B.2}$$

A higher value >2.99 indicates that the firm is not financially distressed. We compute the equity issuance costs for our sample firms according to the cost function estimated in Hennessy and Whited (2007). In their paper, Hennessy and Whited (2007) provide estimates for the equity issuance costs function for small, large and all firms in their sample. At the end of each year, we sort firms according to their size (ME) into tercile portfolios. We then compute the equity issuance costs for the firms in each portfolio for the subsequent year according to the amount of equity that a firm issues in the corresponding year (SSTK). For the firms in the lowest size portfolio, we use the estimation results of Hennessy and Whited (2007) for small firms, for the highest size tercile the estimations for large firms, and for the medium size tercile the estimation results that Hennessy and Whited (2007) obtain for the full sample. We winsorize the estimated equity issuance costs at the 90% level to control for outliers.[17]

The sample period is 1971 to 2010, and all variables are deflated to 1982 dollars using the CPI. Only firms with at least 24 consecutive months of data remain in the sample. Furthermore, we winsorize the sample with regard to the book-to-market ratio, market equity, age, investment, asset sale, and stock returns at the 99% and 1% level. In addition, we exclude firms that have a q below zero or above ten to address issues of investment opportunity measurement in the data. We also require firms to hold at least 5 million dollars in fixed assets to eliminate very small firms. The final sample contains of 3563 firms.

In Table B1, we report some basic sample characteristics. The table reports the mean, the standard deviation (Std), the median, the 25 percent (Q25) and the 75 percent quantiles (Q75). Panel A provides summary statistics for different sample variables of the full sample. In Panel B and Panel C, the table reports the same summary statistics but for bad and good states, respectively. We define an aggregate downturn of our firm economy as years where the sample aggregate sales growth and the annual return across sample firms are in the bottom 25% across all years. We choose this definition of a business cycle downturn mainly because sales growth combined with market based downturn measures are a direct measure of the propagation of positive and negative shocks from the aggregate economy onto the corporate level (see also the downturn definitions in e.g., Opler and

[17]Using the SA-index instead of size as sorting variable does not change the quality of our results.

Titman 1994, Gilson et al. 1990). All other years are defined as good state.

Table B1: **Compustat Sample Summary Statistics**

The table provides summary statistics for different sample variables in Panel A. In Panel B and Panel C, the table reports summary statistics for bad (Panel B) and good (Panel C) states. We define an aggregate downturn of our firm economy as years in which the sample aggregate sales growth and the average annual equity return across sample firms are, simultaneously, in the bottom 25% of all years. All other years are considered as a good state. The table reports the mean, the standard deviation (Std), the median, the 25 percent (Q25), and the 75 percent quantile (Q75). *Total Assets* (*AT*) and *Fixed Assets* (*F*) are in million dollars, measured at the beginning of each year. *Investment* is equal to capital expenditures. *Cash Flow* is the sum of income before extraordinary items and depreciation and amortization. *Asset Sale* are the cash proceeds from sale of fixed capital. *Fin. Slack* is the sum of cash and short-term investments. *Investment*, *Cash Flow*, *Asset Sale*, and *Fin. Slack* are scaled by the book value of the beginning-of-period net fixed assets. *Total debt* is (LT+PSTK-TXDB-DCVT) scaled by *Total Assets*. *Market Equity* is computed as the CRSP monthly share price (PRC) multiplied with the number of outstanding shares (SHROUT). The variable *Cov. Ratio* is computed by dividing *EBITDA* with the interest expenses. The sample period is 1971 to 2010. The sample consists of 3563 U.S. manufacturing firms.

Panel A: Summary Statistics – Full Sample Period					
Variable	Mean	Std	Q25	Median	Q75
TotalAssets (*TA*)	1096.7957	3902.4779	107.9349	248.368	775.2354
Fixedassets (*F*)	341.71	1227.6213	25.3198	65.0605	226.4631
q	1.3736	1.5714	0.3208	0.8114	1.8194
Investment/F	0.2224	0.1267	0.1351	0.1943	0.2769
Asset Sales/F	0.0163	0.0335	0	0.0041	0.017
Cash flow/F	0.3401	0.8763	0.1883	0.3178	0.5115
Fin. Slack/F	0.7944	1.734	0.0777	0.2218	0.6741
Total debt/TA	0.4371	0.1816	0.3061	0.4366	0.5556
Market Equity	1073.251	3124.8059	67.8379	230.3514	774.345
Cov. ratio	50.3956	650.1915	3.8589	7.5978	16.5498
Panel B: Summary Statistics – Bad Business Cycle States					
Variable	Mean	Std	Q25	Median	Q75
TotalAssets (*TA*)	956.4744	3274.8589	104.4335	243.0936	691.5205
Fixedassets (*F*)	321.4881	1116.0169	25.5838	68.6458	223.8184
q	0.7426	1.3518	0.1049	0.2023	0.6972
Investment/F	0.2293	0.1299	0.1402	0.2025	0.2836
Asset Sales/F	0.0166	0.029	0	0.006	0.0196
Cash flow/F	0.3381	0.8569	0.2063	0.3028	0.4566
Fin. Slack/F	0.528	1.4339	0.072	0.1546	0.3511
Total debt/TA	0.4499	0.1652	0.3363	0.4563	0.5574
Market Equity	602.085	2514.0054	18.278	69.1531	341.5384
Cov. ratio	27.3812	178.9324	4.2015	7.5163	14.1713
Panel C: Summary Statistics – Good Business Cycle States					
Variable	Mean	Std	Q25	Median	Q75
TotalAssets (*TA*)	1110.2081	3957.0518	108.067	249.1114	782.224
Fixedassets (*F*)	343.6429	1237.764	25.2956	64.7399	226.5775
q	1.4339	1.5777	0.3726	0.8774	1.9019
Investment/F	0.2217	0.1264	0.1347	0.1936	0.2763
Asset Sales/F	0.0162	0.0339	0	0.0039	0.0167
Cash flow/F	0.3403	0.8782	0.1863	0.3197	0.5177
Fin. Slack/F	0.8199	1.7579	0.0782	0.2343	0.7094
Total debt/TA	0.4358	0.183	0.3028	0.4346	0.5555
MarketEquity	1118.2869	3173.4242	77.0098	248.7331	816.8768
Cov. ratio	52.6282	678.6751	3.8251	7.6041	16.7963

Chapter 5

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